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ABSTRACT

We find that the price volatility of renewable assets is significantly greater than that of brown assets. Our causal estimates leverage the response of electricity and credit markets to US state-level renewable portfolio standards that require some utilities to use renewables while exempting others. This extra risk is related to more volatile electricity prices and revenues, consistent with uncertainties including renewables intermittency. Using a growth model where the share of green capital balances climate damages and diversification benefits, we find that greater green-asset volatility is a more important determinant of economy-wide decarbonization than productivity differences of green versus brown capital.

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1 Introduction

Renewable energy, such as wind and solar, accounts for around 25% of power generation in the US and a similar amount globally (US Energy Information Administration (2023)). Yet, industry practitioners (International Energy Agency (2023), World Economic Forum (2022)) report that investors are wary of owning more of these green assets due to a host of uncertainties, such as intermittency or policy implementation, that lead to more volatile electricity prices and hence revenue streams compared to fossil fuel plants (McKinsey and Company (2024)). Indeed, investors are no doubt aware of recent headlines on issues of renewables in Europe, such as the decrease in wind output in the first quarter of 2025 due to unusually wind-free conditions onshore and offshore (Wall Street Journal (April 25, 2025)).

Just how much extra electricity price and revenue volatility do renewable assets carry? How does this translate to renewable asset price risk? Since the accumulation of renewable assets is crucial to address the damages of climate change, to what extent is the extra asset price volatility then an impediment to economy-wide decarbonization? While the productivity disadvantages of renewables for decarbonization pathways are well understood (see, e.g., IPCC reports such as Rogelj et al. (2018)), renewable asset pricing volatility and its financial and welfare implications have not been addressed.

To confront these issues, we begin by leveraging the response of electricity and credit markets to the implementation of Renewable Portfolio Standards (RPS) to causally infer the extra price risk of renewable assets. Across a number of major carbon-emitting countries, these standards mandate utilities — that typically distribute and generate electricity — to switch from only fossil fuels toward a mix of fossil fuels and renewables such as wind and solar.[1] Since virtually all utilities issue bonds to fund their operations, and have detailed accounting and operational data, we are able to infer financial market perceptions of the extra risk of a firm exposed to renewables from changes in their credit spreads around the implementation of RPS.[2]

An empirical challenge is that the enactment of climate policy is endogenous and dependent on underlying economic conditions that also affect firms' financial health. Hence, the first step in our approach is to exploit institutional features of the RPS system in the United States to estimate its causal effect. Of the 32 states in the US that enacted RPS over the period of 1991-2020, we classify, using various data sources including Barbose (2021), that 14

[1] Emissions trading systems and renewable portfolio standards are two types of regulations used for emissions-intensive sectors, while national carbon taxes are enacted to address gaps for other sectors (see, e.g., Carhart et al. (2022) for an overview of climate policy globally).

[2] Our reliance on the informativeness of credit spreads regarding the impact of climate policy echoes earlier valuable work by Meng (2017) on the use of equity prices to deduce the abatement costs implicit in the Waxman-Markey Bill of 2009-2010.

of them require investor-owned producers (which we refer to interchangeably as corporates) to meet RPS targets but exempt municipal producers.

The municipal-producer exemption allows us, by using panel regressions, to address endogeneity concerns with firm and state-by-year fixed effects. We prefer our within-state methodology to using the staggered implementation of RPS across states (Greenstone and Nath (2020), Upton Jr and Snyder (2017), Deschenes et al. (2023)) to address endogeneity concerns. One reason is that Southeastern states — who tend to be late adopters of RPS — experienced different trends in energy demand, which is particularly problematic for identifying credit-spread effects (Utility Dive (2016), Alabama Public Radio (2023)). Another reason is that we can also verify that there should be no post–RPS differences in outcomes between corporates and municipals in the 18 states without municipal exemptions.

We find that RPS led to not only higher electricity prices but also higher price volatility. Affected investor-owned firms' monthly electricity-price volatility is higher by 4.3 percentage points per annum. While the mean profitability of firms is unaffected due to cost passthrough by regulators, the higher electricity price volatility has a direct association with greater earnings uncertainty and operational risks (Correia et al. (2018)).

Consistent with higher renewables volatility, we then find RPS widens *characteristics-adjusted* credit spreads by around 69-100 bps, which is robust across a variety of specifications.[3] In other words, the extra renewables risk is not passed through by regulators to consumers, but is borne by firms and investors. We rule out alternative explanations, such as changes in firm leverage or liquidity (Merton (1974)). Even as we do not have traded equity values for utilities, we are able to impute asset volatility using our observed credit spreads, the structural corporate bond pricing model of Longstaff and Schwartz (1995), and data on the mix of renewables mandated by RPS. To match our conservative estimate of wider credit spreads for RPS-affected firms, we impute a renewable asset volatility of around 1.7 times that of fossil fuel assets, roughly 39% compared to 23%.[4]

To understand the importance of renewables volatility for decarbonization at the economy-wide level, we consider—as a first pass—the planner's solution of a two capital growth model in continuous time along the lines of Eberly and Wang (2010), in which society balances climate damages with the diversification benefits of having both green and brown assets or capital. Households with Epstein and Zin (2013) preferences and firms invest in two types of capital —brown and green —each producing the same final good, but subject to distinct

[3]Following Daniel et al. (1997), these yields are adjusted for issue-level characteristics including credit ratings, issue amount, maturity, and in the case of municipal debt, its purpose and tax treatment.

[4]Our estimate accounts for the financial market's perception of the volatility of fossil fuel assets, which depend primarily on oil prices, and the effectiveness of hedging renewables volatility on the part of producers, such as by using batteries or specialized gas plants, known as peaker plants, to address intermittency issues.

stochastic processes.

Differences in the volatility of the diffusion shocks to the two types of capital capture the higher renewables volatility associated with a host of uncertainties.[5] We also incorporate 'disaster' shocks that capture the threat of climate-related damages: if the economy relies too heavily on brown capital, the arrival rate of damaging climate events increases. By introducing this disaster process so that rising green capacity lowers the occurrence of catastrophic climate outcomes, we allow for an endogenous mechanism wherein more green investment reduces climate risk (Hong et al. (2023b), Nguyen et al. (2024)).[6]

We assume that green and brown assets differ in terms of their climate externalities, productivities and volatilities. We calibrate our model to macro-financial moments and climate damages from disasters. Importantly, risk preferences are calibrated to match a high equity risk premium and a low risk-free rate (Bansal and Yaron (2004)). As green investment becomes riskier, the representative investor values more brown capital for diversification reasons even though these investments accelerate climate damage. This means that the equilibrium outcome features a notably smaller share of green capital than would be expected if both capital types had similar volatilities.

In our calibration, we find that the proportion of green capital in the economy encompassing power, manufacturing, and transportation, which is currently around 20%, would increase to around 48% absent the higher renewables volatility. An assumption in our calibration is that the difference in the volatility of green to brown capital is proportional to our estimate in the power sector.[7] Even if green capital were twice as productive as brown capital—despite estimates placing it 30–40% lower—the share of green capital would still only reach around 25% in the presence of heightened green volatility.

Hence, the model identifies a crucial channel —renewable portfolio risk—or a second moment effect that can be an impediment to renewable investment and a drag on welfare. Even severe climate damages, or more productive green capital, do not guarantee an overwhelmingly large green sector when the latter's price volatility is significantly higher. The tractability of our continuous-time model allows us to highlight the economic rationale. By applying Itô's lemma to obtain the equilibrium share of green capital in the economy, we

[5]The extra risk of renewable asset prices might also be due to other features such as renewables being a nascent technology in contrast to mature fossil-fuel technology.

[6]In the limit when there is only one type of capital, the model collapses to the Pindyck and Wang (2013) single-sector representation. This nesting is useful both for theoretical clarity (showing how the standard single-sector climate economy model emerges within the two-sector approach), and aids in practical calibration.

[7]We think this is a reasonable baseline as intermittency, nascent technology or regulatory uncertainty also matter for green capital in other sectors. For instance, Bena et al. (2023) find that banks charge a higher interest rate for loans to finance green car purchases than brown car purchases.

deduce that the reason has to do with the diminishing effects of higher productivity on investment due to convex adjustment costs versus a diversification penalty that scales linearly with the volatility of green capital.

Related literatures. The literature on climate finance (see Hong et al. (2020), Giglio et al. (2021), Van der Ploeg and Rezai (2020), and Acharya et al. (2023) for reviews) focuses on the first moment of brown asset values or stranded assets; carbon regulation might lead these asset values to decline and green assets might be a hedge against transition risk (Rozenberg et al. (2020), Cahen-Fourot et al. (2021), Fried et al. (2022), Barnett (2019), Sen and Von Schickfus (2020), Pástor et al. (2022), Bolton and Kacperczyk (2020)). We show that the second moment of green assets plays an equally important role in the green transition, by advancing the identification and quantification of renewable asset pricing risk.

Specifically, we exploit policy-induced (RPS) variation to identify this additional source of financial risk. Our within-state empirical design contributes to earlier important work on RPS, which exploits cross-state identification procedures (Greenstone and Nath (2020), Upton Jr and Snyder (2017), Deschenes et al. (2023)) to show that RPS led to higher renewables asset accumulation and that the costs are passed onto consumers in the form of higher electricity prices.

And our quantitative model also contributes to the literature on integrated assessment models of climate policy (Nordhaus (2017), Golosov et al. (2014), Jensen and Traeger (2014)), by exploring the impact of higher renewable asset price volatility on decarbonization pathways. Our work complements recent contributions that demonstrate the importance of modeling uncertainties for optimal climate policy (Barnett et al. (2022) Barnett et al. (2020), and Hong et al. (2023a) Barnett et al. (2024)).

Finally, the industrial organization literature has modeled the higher costs associated with intermittency in renewable electricity production (Joskow (2011), Hirth et al. (2015), Gowrisankaran et al. (2016), Butters et al. (2021)) and pointed to uncertainties in policy implementation. Our approach adds to this literature by showing that these uncertainties also manifest as higher asset price volatility for renewables, which in turn constrains their share in the socially optimal energy mix due to a diversification channel.

2 Background and Data

Historically, the main entities in the US power sector have been investor-owned utilities, municipal utilities and cooperative utilities.[8] In practice, municipal and cooperative utilities (which are typically located in rural areas) are treated similarly by bond markets and we will describe them as municipal utilities. Most utilities, especially investor-owned, were vertically integrated, providing both generation and distribution of power to consumers.[9] This vertical integration created a natural monopoly, necessitating that all aspects of the activities of utilities be regulated by state regulatory commissions.

We consider several measures of asset price volatility for utilities, which are ultimately tied to whether their assets are based on fossil fuels or renewables. Since utilities issue debt, our first and most important measure is the credit or yield spreads of their debt issuance. Furthermore, we can use company financials such as earnings or volatility of earnings to capture asset price volatility. It can also be tied to operational risk in the form of volatile product or electricity prices. We describe how we construct these measures below.

2.1 Investor-owned versus municipal producers

We use two data sources to determine whether a state's RPS program regulates the emissions of investor-owned utilities differently than other utilities. One of the major groups of firms that are exempt in a fraction of states are municipal producers. But in general, state exemptions can apply even to a single name, though these instances are rare. The first source is Barbose (2021). We then crosscheck the descriptions of state RPS programs there with a second source: the Database of State Incentives for Renewables and Efficiency (DSIRE). This website is maintained by the North Carolina Clean Energy Technology Center at North Carolina State University and contains descriptions of each state's RPS program. As part of these descriptions, the website indicates which types of utilities are covered by the RPS.

For states that only include investor-owned firms in their RPS mandate, it is an easy call to classify them as part of our sample of states that differentially treat utilities. But there are a handful of states that are more complicated. There are a few states that have more stringent mandates for investor-owned firms than other utilities. For example, in Colorado in 2022, investor-owned utilities were required to meet a 30% RPS target, but municipal utilities only had to meet a 10% target. We include such states that have higher mandates for investor-owned utilities in our municipal-exempted sample. Also, a handful of states

[8]For more detailed descriptions of the US power sector, see, for example, DOE (2015), Garofalo (2021), and Joskow (2024).

[9]Municipal utilities often do not generate their own electricity and buy it on the wholesale market.

Table 1: Summary of RPS Legislation in States with Municipal Exemptions

This table presents summary details of the passage of Renewable Portfolio Standards regulation in the states that have thus far enacted the legislation with exemptions for municipal producers. Arizona and Hawaii also have RPS but we exclude them from our analysis since they have no municipal producers. For the number of municipal and investor-owned producers, and their sales in gigawatt hours, we take the time series average.

State	Mandate Start	Maximum Green %	Year Max Achieved	No. Investor-Owned	No. Municipal	Investor-Owned Sales (GWh)	Municipal Sales (GWh)
Colorado	2004	30	2020	1.65	8.4	29,681	21,985
Iowa	1991	1	2000	2.15	57.3	34,440	11,353
Illinois	2007	25	2026	4.2	18.4	64,389	12,779
Kansas	2009	20	2020	4	45.9	26,207	13,239
Minnesota	2007	30	2020	3.65	46.15	42,043	23,566
Missouri	2008	15	2021	2	2.05	55,855	23,964
North Carolina	2007	12.5	2021	3	2.95	96,840	33,076
New Hampshire	2007	12.8	2025	1.8	1	7,019	857
New Mexico	2004	80	2040	3	2.55	14,973	7,079
Ohio	2008	8.5	2026	8.25	14.75	73,896	17,670
Oregon	2007	50	2040	4.6	1	30,363	15,779
Virginia	2020	100	2050	3.2	8.55	85,474	23,972

treat different types of investor-owned utilities differently. For example, in Virginia, the RPS only covers the two large investor-owned utilities in the state and not a handful of smaller investor-owned utilities. We classify the entire investor-owned sector in states such as Virginia as being covered by the mandate.

States with and without municipal-producer exemptions. In Table 1, we report the RPS details for the states that exempted their municipal producers. Many of these states implemented their RPS in the mid-to-late 2000s. Investor-owned producers are allowed to gradually ramp up their mix of renewables before hitting the required or steady-state amount. Justifications for the exemption include that municipal producers do not cause as much damage to the climate in the first place (Lyon and Yin (2010), Carley and Miller (2012)). Such ideological motivations are similar to the sorts of policy variations used in the studies of European climate policies by Känzig (2021) and Metcalf and Stock (2020) for identification.

Consider the state of Illinois, which implemented its RPS in 2007. It gave firms a runway of around 20 years to reach a required renewable mix of 25% of output. Hence, investor-owned producers had to increase their mix by roughly a percent a year. States typically vary the length of the transition period to a steady-state requirement depending on how stringent those requirements are.

In Table 1, we also report for each state the time-series average of the number of producers of each type and the time-series average of the total sales of the two types of supplier.

Investor-owned firms mostly operate in one state, but around 5.4% operate in more than one state. While there are a greater number of municipal producers compared to investor-owned ones, investor-owned suppliers' sales are much higher than those of the municipal producers. For instance, in the state of Illinois, there are on average in a typical year around 4.2 investor-owned producers who sell 64,389 gigawatt hours. There are 18.4 municipal producers who sell 12,779 gigawatt hours.

In Table O.1 in the Online Appendix, we report summary statistics for the other states with RPS but that do not exempt their municipal producers. Other than the municipal exemption, the distributions of mandate start dates, maximum green requirements, and year the maximum target is achieved are not dissimilar to those from the states with exemptions.[10]

2.2 Electricity pricing and producer performance

Electricity price data. Data for electricity prices is not broken down at the producer level. Instead, we collect monthly data on the *average* retail price of electricity from investor-owned and municipal utilities (separately) from 2001 to 2021. To deal with outliers, we winsorize at the 5% level. These data come from various years of EIA State Electricity Profiles and are measured as cents/kWh.[11] We aggregate these prices to the annual level by taking the average across all months in each year. Electricity prices are fairly similar for investor-owned and municipal operators (9.2 vs. 8.7 cents per Kilowatt hour, respectively) across the entire sample.

Electricity price volatility. For price volatility, we construct the log difference in prices from month to month for each state and producer-type pair. We then take the standard deviation of these log changes at the annual level. This gives us, for each producer-type in each state in each year, a single observation of price volatility, which we label σ^p. The volatility of electricity pricing is slightly larger for investor-owned operators compared to their municipal peers (4.8% vs. 3.9%) over the full sample period.

2.3 Debt issues

Corporate bonds. We draw our data for corporate bonds from Mergent FISD, a standard corporate bond database. This dataset contains information on the yields, maturity, issue amount, bond rating, industrial sector, and issuer name of corporate bond issues in the

[10] As in the case of Arizona and Hawaii, there are no municipal producers in D.C., Maine, Montana, Nevada, and Rhode Island, so we also omit observations from these states in all of our analyses.

[11] The EIA collects from producers their revenue and production data, thereby allowing them to back out average electricity prices.

Table 2: Summary Statistics– Electricity Pricing Data

This table presents summary statistics on electricity pricing data. The data we collect runs from 1990 to 2021. The frequency is annual. Electricity Price and Electricity Price Volatility are at the producer type-level, i.e. aggregated at the 'Investor-Owned' and 'Municipal' level.

	Investor-Owned				Municipal			
Variable	N	Mean	SD	Median	N	Mean	SD	Median
Electricity Price (cents/kWh)	209	9.2	2.8	9	145	8.7	1.7	8.9
log(Electricity Price)	209	2.2	0.27	2.2	145	2.1	0.2	2.2
Electricity Price Volatility, σ^p	209	4.8%	2.6%	4.2%	145	3.9%	2.4%	3.4%
Net Income Volatility, σ^{NI}	314	36%	35%	25%	17	62%	59%	29%

United States, plus a host of other issue-relevant variables. We filter on firms in the power sector. Although this data contains information on the state of the head office of the issuer, it does not typically contain information on the state or states in which the issuer operates.

To address this issue, we integrate our bond data with our dataset on utility operations, the details of which are outlined above. We match these two databases using the legal name of the issuer, as given in the 'Bond Issuers' dataset within Mergent, and perform a string-distance match with our production dataset. We are able to perform an exact match to roughly a third of issuers from Mergent, though these issuers make up roughly 72% of all issues in our dataset. When we cannot match exactly, we assume that the state of operation is the same as the state of the head office.[12] In a robustness check, we run our analysis on only the issuers we are able to match exactly; our results are essentially unchanged.

One technical issue with analyzing at the issue level is that many investor-owned utilities operate across several states. To resolve this problem, and ensure that issues are appropriately assigned to states, we perform the following procedure: first, we calculate the average exposure of an investor-owned utility in each of the states where it has a presence by taking the time-series total of sales in each state and dividing by the total sales across all states. For a utility with a presence in only one state, this results in a value of 1.

We then replicate any issues for utilities that operate in multiple states, but weight that observation by the previously calculated exposure. Therefore, if utility 'A' operates in, for example, Kansas, Kentucky, and Tennessee, and has sold roughly 20%, 20%, and 60% of its output in each state respectively, then an issue from utility 'A' appears three times in our dataset, with one assignment to each state, where each observation is weighted by 0.2, 0.2, and 0.6 respectively.

[12] By looking at the discrepancy between the state of operation and state of the head office in our exact matches, we find that this assumption is correct roughly 87% of the time.

Table 3: Summary Statistics of Bond Issue Level Data

This table presents summary statistics on our final dataset of bond data. The data we collect runs from 1990 to 2021. Adjusted Yields are constructed using a characteristic benchmarking approach as described in Section 2.3.1. Tax code refers to one of four options: CB is taxable corporate bond, E is municipal bond exempt from federal tax, A is municipal bond taxable subject to AMT (Alternative Minimum Tax), and T is taxable municipal bond. Security Type refers to one of three options: CB is simply for corporate bonds, GO is general obligation municipal bond, and RV is revenue municipal bond.

	Investor-Owned			Municipal		
Variable	N	Mean	SD	N	Mean	SD
Yield	1,745	0.058	0.019	302	0.043	0.014
Maturity (years)	1,745	16	11	302	19	7.1
Issue Amount ($mn)	1,745	244	233	302	52	104
Moody Rating (rank)	1,745	6.6	2.5	302	1.3	1
Investment Grade	1,745	0.95	0.21	302	1	0
Observations in Post Period	1,745	0.39	0.49	302	0.26	0.44
Adjusted Yield	1,745	0.00089	0.014	302	-0.0073	0.015
Year	1,745	2004	9.7	302	2002	5.6
Security Type	1,745			302		
... CB	1,745	100%		0	0%	
... GO	0	0%		32	11%	
... RV	0	0%		270	89%	
Tax Code	1,745			302		
... A	0	0%		8	3%	
... CB	1,745	100%		0	0%	
... E	0	0%		261	86%	
... T	0	0%		33	11%	

Municipal bonds. For municipal bonds, we use the SDC Muni database. This dataset contains information on the yields, maturity, issue amount, bond rating, industrial sector, state, and issuer name of municipal bond issues in the United States, plus a host of other issue-relevant variables. Given our interest in assessing the impact of RPS, we restrict attention to municipal bond issues in the 'Electric & Public Power', 'Combined Utilities', and 'Gas' sectors. Across our sample period of 1990 to 2021, we find complete data on 2,049 municipal issues.

2.3.1 Comparing investor-owned and municipal bond issues

Unsurprisingly, municipal bond issues differ in systematic ways from investor-owned bond issues. Table 3 reports the mean and standard deviation of the variables of interest by municipal versus investor-owned issues. First, we have 302 issues by municipals, versus 1,745 corporate issues. For both types of producers, we find there are more debt issues for investor-owned utilities than municipals post RPS — 39% compared to 26%.

The typical municipal debt issue is 52 million dollars with a standard deviation of 104 million dollars. For investor-owned, the mean is 244 million dollars, with a standard deviation of 233 million dollars. Municipals borrow at longer maturities — 19 years, compared to 16 years for investor-owned. The mean yield of municipal issues is 4.3%, while it is 5.8% for investor-owned. The standard deviation of yields is also larger for investor-owned, 1.9% compared to 1.4% for municipals. This difference in yields reflects the fact that municipals typically have a higher Moody's rating, 1.3 compared to 6.6 for investor-owned.[13] All municipal debt is investment grade, while 95% of the investor-owned debt is investment grade.

Characteristics-adjusted bond yields. Since systematic differences exist between municipal and investor-owned issues that could distort our findings, we perform an adjustment to bond yields at issuance using a characteristics-based benchmarking as in Daniel et al. (1997). Specifically, we form 5x5x5 portfolios based on Moody's ratings, maturity, and issue size for adjusting yields. For each of these 125 portfolios, we calculate the median yield at issuance. We then subtract this median yield from the yields of all bonds within the same grouping. The means and standard deviations of these characteristics-adjusted yields are also given in Table 3. The resulting distributions are shown in Figure O.1 in the Online Appendix. This figure shows that the two distributions after adjustment are not too far

[13]Here a value of 1 corresponds to Aaa, and a value of 17 corresponds to Caa1. A value of 7 indicates a Moody's rating of A3.

apart from each other.[14]

In addition to issue amount, maturity, yield, and credit rating information, we also have information on the tax treatment of the various bonds as well as the security type. As corporate bonds do not vary in their tax codes, nor do they have specified purposes as is the case for municipal bonds, we simply assign a single tax and security type identifier to these issues.

3 Electricity Price Volatility and Asset Prices

We begin by analyzing how electricity prices respond to the introduction of Renewable Portfolio Standards (RPS) by exploiting within-state variation using municipal-producer exemptions. Our empirical strategy compares utilities subject to RPS with exempted municipal utilities in the same state, allowing us to isolate the policy's effects while accounting for state-level trends.

This approach has several advantages. Investor-owned (corporate) utilities and municipal utilities are more likely to be subject to the same state-level economic and regulatory forces, making them natural within-state comparators. Moreover, since they operate in segmented product markets, competitive spillovers are less likely to confound our identification strategy. Estimating our effects at the state level also helps address concerns related to two-way fixed effects estimation (Sun and Abraham (2021), Goodman-Bacon (2021)). Finally, because municipals and corporates differ in ways that are largely fixed over time, the exclusion restriction is plausible, provided we control for these fixed differences using firm or producer fixed effects or adjustments such as characteristics-adjusted bond yields.

Having established the effect of RPS on electricity prices, we then examine whether these changes translate into financial market responses. Specifically, we ask: Do asset prices reflect the increased volatility in electricity prices? To answer this, we analyze the response of credit spreads, using bond issuance data to test whether RPS-induced uncertainty is priced into corporate debt markets. Our empirical approach parallels the electricity price analysis, leveraging the same within-state design to compare investor-owned utilities to their exempted municipal counterparts.

Non-exempt states. As a test of the validity of our approach, we run the same exercises as in our main analyses, but restrict to the states that did not allow municipal exemptions.

[14] An additional significant distinction between municipal and corporate bonds lies in their callability. Although adjusting for this difference can be challenging, it should not impact the identification process as long as the rates of callability remain relatively stable over the period in question.

If our main finding is robust, we should not see a significant difference in corporate outcomes relative to municipalities in the same state-year following the implementation of RPS legislation in those states.

3.1 Electricity Prices

Understanding how RPS affects electricity prices is a crucial first step in assessing its broader economic impact. If the costs of renewables are passed through to consumers, we would expect an increase in average electricity prices. However, beyond changes in price levels, RPS may also introduce greater volatility in electricity prices. Increased price volatility raises earnings uncertainty, as fluctuations in product prices are strongly linked to earnings volatility (Correia et al. (2018)).

Mean electricity prices. To assess the impact of RPS on mean electricity prices, we use the following difference-in-differences design:

$$\log p^e_{q,s,m} = \alpha_{s,t} + \phi_q + \beta corp_q \times post_{s,t} + \Gamma K_{q,s,t} + \epsilon_{q,s,t} \tag{1}$$

where $\log p^e_{q,s,m}$ is the log of the average monthly retail electricity price (cents/kWh) of producer-type q in state s, and $corp_q$ is an indicator that takes a value of one if the price in question is for the investor-owned sector. We use a single state-year fixed effect, $\alpha_{s,t}$. We include the following controls, interacted with the 'investor-owned' dummy: the pre-RPS average producer-type capacity and electricity sale price, the level of the RPS mandate in the state at each year, and a set of indicators that denote the climate categorization of the state, as defined by the National Oceanic and Atmospheric Administration (NOAA), to account for regional differences in electricity markets.

The key coefficient is on the interaction term between $corp_q$ and $post_{s,t}$ (β). This coefficient captures the average differential response of log electricity prices, $\log p^e_{q,s,m}$, between investor-owned and exempted municipal operators in the period after the passage of RPS. We also conduct an event study design using the following specification:

$$\begin{aligned}\log p^e_{q,s,m} = &\alpha_{s,t} + \phi_i + \beta_{-5} D_{r_{s,t} \leq -5} \times corp_q + \sum_{-4 \leq r_{s,t} \leq -2} \beta_r D_{r_{s,t}} \times corp_q \\ &+ \sum_{0 \leq r_{s,t} \leq 14} \beta_r D_{r_{s,t}} \times corp_q + \beta_{15} D_{r_{s,t} \geq 15} \times corp_q + \Gamma K_{q,s,t} + \epsilon_{q,s,t}\end{aligned} \tag{2}$$

We include the same vector of controls as in our static difference-in-differences, again interacted with the investor-owned producer-type dummy ($corp_q$). The only difference between

Table 4: Electricity Price Effects– Difference-in-Differences

This table presents results from a difference-in-differences estimation that examines the impact of RPS on average electricity prices and electricity price volatility. In Panel A, we show summary statistics of average prices and our measure of pricing volatility. In Panel B, we show the regression results using producer-type observations at the yearly level.

Dependent Variable:	$\log p^e$	σ^p
Model:	(1)	(2)
Variables		
corp × post	0.0667***	0.0124**
	(0.0165)	(0.0059)
Controls	Yes	Yes
Fixed-effects		
State-Year	Yes	Yes
Fit statistics		
Observations	354	354
R^2	0.98680	0.83949
Within R^2	0.85830	0.67964

Clustered (State-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

the expression in Equation 2 and the one in Equation 1 is that we expand the variable $post_{s,t}$ into a series of relative time indicators, $D_{r_{s,t}}$. These indicators take a value of one if the observation in year t is r years relative to the passage of RPS in state s. The advantage of the specification outlined in Equation 2 is that it allows us to test for pre-trends, and also sheds light on how the impact of RPS is expressed over time.

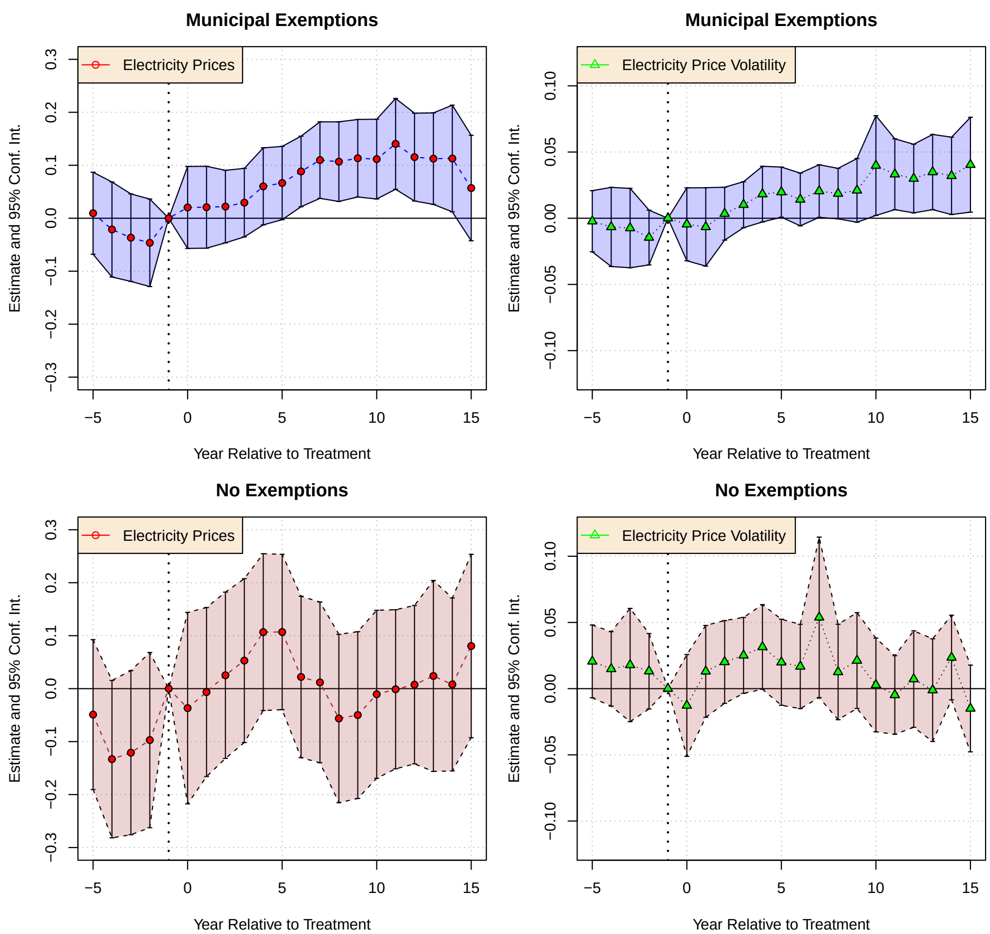
Our results for the simple difference-in-differences can be found in Column (1) of Table 4. RPS leads to around 6.7% higher electricity prices, with a statistical significance at the 1% level.[15] The results from the event study design can be seen in the left column of Figure 1. We include estimates for states with municipal exemptions (top row) and without exemptions (bottom row). In the top row, for the affected firms, there is a gradual upward drift of electricity prices post RPS. There is no such pattern for the states without exemptions. There is a clear contrast in the patterns across these two samples which provides further evidence that RPS was responsible for increases in electricity prices.[16]

[15]Compared to existing literature that uses an across-state design, we find smaller estimates for price effects: Upton Jr and Snyder (2017) find electricity price increases of between 10.9-11.6%, and Greenstone and Nath (2020) find that prices increased by 11%.

[16]In Appendix A, we confirm that the electricity price increase corresponds to a complete pass through of the costs of mandated renewable investments to consumers.

Figure 1: Electricity Prices– Event Study

In this figure, we plot the results of our event study specification looking at electricity price and price volatility. We use producer-type observations at the yearly level. In all specifications, we control for the pre-RPS average producer-type capacity and electricity sale price, the level of the RPS mandate in the state at each year, and the climate of the state. Results for the log of prices are shown in the left column, and for price volatility in the right column. We bin all observations longer than 5 years before RPS passage. We include estimations using states with municipal exemptions (top row, blue, solid confidence interval lines) and using states without exemptions (bottom row, brown, dashed confidence interval lines). Confidence bands are given at the 95% level.



Volatility of electricity prices. To assess the effect of RPS on the volatility of electricity prices, we first estimate a difference-in-differences design using Equation 3, where we let $\sigma^p_{q,s,t}$, the price volatility of producer-type q operating in state s in year t, be the dependent variable. We include the same set of controls as before: pre-RPS averages of power capacity and electricity prices, the level of the RPS mandate in the state at each year, and an indicator for the state's climate.

In Column (2) of Table 4, we find a positive and significant coefficient on $corp \times post$, consistent with electricity prices becoming more volatile for investor-owned utilities compared to the municipal control. The monthly volatility of affected utilities' electricity prices is higher by 1.24 percentage points. This would translate to a difference annually of 4.3 percentage points.

In the right column of Figure 1 we plot the results using states that passed municipal exemptions. We find no evidence of a pre-trend. We also find strong evidence of increased price volatility over an extended time frame. The standard error bands are quite tight for years $t = 5$ to $t = 15$ in the post-RPS sample. Reassuringly, we find no meaningful impact for states without municipal exemptions, as illustrated by the bottom row of Figure 1.

Volatility of firm earnings. In the Online Appendix, we confirm that the increased electricity price volatility translates into greater earnings volatility (Section O.1). We observe no significant negative impact of RPS on mean corporate earnings, but a significant increase in the volatility of net income of investor-owned utilities in the post-RPS period. An important caveat is that earnings data is quite infrequent and sparse, hence we view this analysis only as rough confirmation of our volatility mechanism. A far better method is to impute asset volatility from credit spreads using a structural bond pricing model, which we explore in Section 4.

3.2 Response of Credit Spreads

Given that RPS increases the volatility of electricity prices and firm earnings, a natural question is whether these effects are reflected in financial markets. In particular, if electricity price volatility translates into greater earnings uncertainty for utilities, we would expect this risk to be priced into asset markets. We test this by examining the response of credit spreads, using bond issuance data to assess whether investors demand higher yields from investor-owned utilities relative to their exempted municipal counterparts in the post-RPS period.

3.2.1 Baseline estimates

Our estimation specification is described by Equation 3, where the dependent variable, $y_{i,j,s,t}$, is the adjusted yield of issue j, for firm i, operating in state s, issued in year t:

$$y_{i,j,s,t} = \alpha_{s,t} + \phi_i + \varphi_j + \tau_j + \beta corp_i \times post_{s,t} + \Gamma K_{i,j,s,t} + e_{i,j,s,t} \tag{3}$$

where $corp_i$ is an indicator that takes a value of one if the bond issuer is investor-owned and must comply with RPS mandates, $post_{s,t}$ is an indicator that takes a value of one if the observation at year t is after the passage of RPS in state s, $\alpha_{s,t}$ is a state-year fixed effect, ϕ_i is an issuer fixed effect, φ_j is a security type fixed effect, and τ_j is a tax code fixed effect.[17] We control for the log of maturity, the log of the issue amount, and the ratings band of the issue. We include both raw controls, and controls interacted with the corporate dummy ($corp_i$).

Our results are shown in Column (1) of Table 5. We find evidence that RPS led to higher yield spreads for corporate issuers of around 98 basis points. Given that the standard deviation of adjusted yields for investor-owned firms is 140 basis points (Table 3), RPS led to a large 0.7 standard deviation increase in characteristics-adjusted yield spreads. Considering the importance of this estimate, we also consider a state-by-state estimation design to avoid the problem of two-way fixed effects entirely and to better gauge the robustness of our estimate.

3.2.2 State-by-state estimates

Given that states that pass RPS with exemptions for municipal producers have a natural treatment and control group, we can also estimate yield effects for each state separately and then aggregate them. We do this by running the following specification for each s of the 12 states with municipal exemptions in our sample:

$$y_{i,j,t} = \phi_i + \vartheta_t + \varphi_j + \tau_j + \beta_s \left(corp_j \times post_t\right) + \Psi \mathbf{K}_{j,t} + e_{j,t} \tag{4}$$

Note that we no longer include a state-time fixed effect, as we are comparing within state by construction. Instead, we use a separate time fixed effect (ϑ_t). We use the same set of controls as when we obtain our baseline estimates. This procedure then generates a set of $\{\beta_s\}$ coefficients, one for each state in the sample.

[17] The security type of issue j takes a value of CB for corporate bonds, GO for general obligation municipal bonds, and RV for revenue municipal bonds; the tax code takes a value of CB for corporate bonds, A for municipal bonds taxable subject to AMT (Alternative Minimum Tax), E for municipal bonds exempt from federal tax, and T for taxable municipal bonds.

To generate a state-level coefficient, we require that there is at least one bond issuance by an investor-owned and a municipal operator both before and after RPS passage. This is true for seven of the twelve states we include: Colorado, Illinois, Kansas, Minnesota, North Carolina, Ohio, and Oregon. For Iowa, Missouri, New Hampshire, New Mexico, and Virginia, we are unable to generate coefficients. As such, the weighted average of state-by-state results is restricted to only including coefficients from the former seven states.[18]

We aggregate by taking a weighted average using the inverse of the standard error of the coefficient (precision weighting). We construct the standard error using the following formula:

$$\text{Variance of } \hat{\beta}_{weighted} = \frac{1}{\sum_i w_i^2} \tag{5}$$

where w_i is the weight for the i^{th} estimate, i.e., the precision weight (the inverse of the variance, σ_i^2). This is the standard inverse-variance weighting formula, assuming independence in the coefficients (Hartung et al. (2011)).

In Column (2) of Table 5, we find a statistically significant and positive coefficient for adjusted yields of 156 bps. The magnitude is higher than in our findings using the entire sample and controlling for a state-year fixed effect, as in the standard difference-in-differences approach (Column (1) of Table 5).

3.2.3 Triple difference-in-differences estimates

By pooling observations from exempt and non-exempt states and running a panel regression specification that compares the difference-in-differences estimates for exempt versus non-exempt states, we arrive at a triple difference estimate that places the effect conservatively at 69 bps. This latter design addresses concerns that unobserved differences in features of corporate versus municipal bonds are somehow correlated with the timing of RPS implementation.[19]

In Column (3) of Table 5 we present our results. Consistent with our identification, we do not find a significant impact of RPS on corporate-bond versus municipal-bond spreads in states without exemptions (the coefficient on $corp_i \times post_{s,t}$ is not statistically significant). By contrast, we find a positive and statistically significant coefficient of 69bps for the spread in adjusted yields for states with exemptions.[20]

[18] This only reduces the number of observations in our sample from 2,047 to 1,570, as can be seen in Column (2) of Table 5. This is because the five excluded states are either small in terms of investor-owned and municipal sales (New Hampshire and New Mexico), pass RPS very early (Iowa, 1991) or very late (Virginia, 2020) in the sample, or have few municipal producers (Missouri).

[19] Bonds differ in many features such as callability that are not easily controlled for due to potential missing data.

[20] Our causal estimate that climate policy impact credit spreads is supported by Ivanov et al. (2023), who

Table 5: Bond Credit Spreads Difference in Differences

This table presents results from three difference-in-differences estimation designs that examine the impact of RPS on adjusted yields. In Column (1) we estimate the standard difference-in-differences specification outlined in Equation 3. In Column (2) we aggregate individual state-level regressions into a weighted average. We estimate Equation 4 for each of the 14 states that passed RPS with a municipal exemption, then aggregate these using inverse-variance (precision) weights. Standard errors are constructed using Equation 5. In Column (3), we pool issue level observations from all 32 states that passed RPS legislation. We include an indicator, $exempt_s$, that takes a value of 1 if the state instituted a municipal supplier exemption. The coefficient on $corp \times post$ captures the change in post RPS legislation spreads between corporate and municipal suppliers in states without municipal exemptions, and the coefficient on $exempt \times corp \times post$ captures the differential effect in states with exemptions. We include the log of maturity, the log of the issue amount, and the Moody rating rank as controls in all three regressions. Yields are adjusted using the procedure outlined in Section 2.

Dependent Variables:		Adjusted Yields	
Model:	(1)	(2)	(3)
Variables			
corp × post	0.0098***	0.0156***	0.0024
	(0.0029)	(0.0018)	(0.0023)
exempt × corp × post			0.0069*
			(0.0038)
Controls	Yes	Yes	Yes
Fixed-effects			
State-Year	Yes		Yes
Year		Yes	
Issuer	Yes	Yes	Yes
Security Type	Yes	Yes	Yes
Tax Code	Yes	Yes	Yes
Fit statistics			
Observations	2,047	1,570	6,543
R^2	0.70231	n/a	0.72671
Within R^2	0.15566	n/a	0.13138

Clustered (State-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

3.2.4 Event-study specification

We then estimate an issue-level regression using the specification outlined in Equation 6:

$$\begin{aligned} y_{i,j,s,t} =& \alpha_{s,t} + \phi_i + \varphi_j + \tau_j + \beta_{-5} D_{r_{s,t} \le -5} \times corp_i + \sum_{-4 \le r_{s,t} \le -2} \beta_r D_{r_{s,t}} \times corp_i \\ &+ \sum_{0 \le r_{s,t} \le 5} \beta_r D_{r_{s,t}} \times corp_i + \beta_6 D_{r_{s,t} \ge 6} \times corp_x + \Gamma K_{i,j,s,t} + e_{i,j,s,t} \end{aligned} \tag{6}$$

As in the case with electricity price, the only difference between this approach and the standard difference-in-differences design is the expansion of the variable $post_{s,t}$ into a series of relative time indicators, $D_{r_{s,t}}$. Again, these indicators take a value of one if the observation in year t is r years relative to the passage of RPS in state s.

We bin all observations after 6 years due to declining numbers of municipal bond observations. In some cases, we do not have sufficient variation of corporate and municipal bond issuances within states to generate reasonable coefficients. Hence, by binning at 6 years, we can still produce a meaningful coefficient that reflects the long-term yield impact of RPS.

We plot the event studies from our estimations for states with and without exemptions in Figure 2. Specifically, we plot the values of the fitted coefficients, $\{\beta_{-5}, ..., \beta_6\}$, that capture the differential response of corporate (affected) to municipal (exempted) producers after the RPS mandates. The figure in the left panel shows our findings at the issue-level for states that instituted municipal exemptions. Reassuringly, we find limited evidence of significant pre-trends. Since there are no pre-trends in bond yields, it means that bond markets did not anticipate the differential treatment of investor-owned utilities. For states with municipal exemptions (left column in blue), we see an economically and statistically significant impact on bond yields. There is a steady increase in yield spreads that persists in the long-run (β_6 is positive and statistically significant).

In the right panel of Figure 2 (in brown), we re-run our analysis for the 18 states that enacted RPS legislation without municipality exemptions. Consistent with the validity of our identification strategy, we do not observe any significant response in the credit spreads of investor-owned bond issues relative to municipalities in those states.

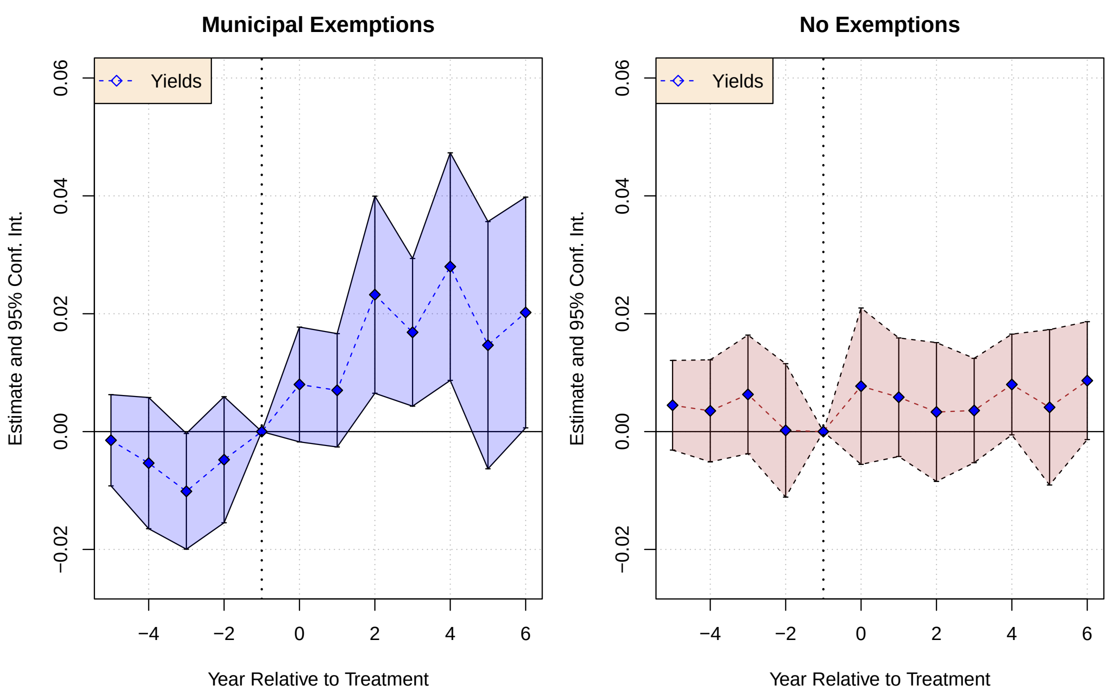
3.2.5 Ruling out Alternative Explanations

The increase in yield spreads following RPS could, in principle, be driven by several factors. As pointed out by studies in the empirical pricing of corporate bonds (Huang and Huang (2012), Collin-Dufresn et al. (2001)) following Merton (1974), there can be four potential

find that bank lending tightens for firms subject to California greenhouse gas policies.

Figure 2: Adjusted Yields in States with and without Exemptions– Event Study

In this figure we plot the results of our event study specification assessing the dynamic impact of RPS passage on adjusted bond yields at issuance. We estimate the specification outlined in Equation 6. We include results for states with municipal exemptions (left panel, blue, solid confidence interval lines) and without exemptions (right panel, brown, dashed confidence interval lines). We adjust yields using the procedure outline in Section 2.3.1. Confidence bands are given at the 95% level. We bin all observations outside of the endpoints.



explanations for why yield spreads of affected firms might have risen following the imposition of RPS: (i) an increase in asset value volatility, (ii) a decline in firm asset values, (iii) higher corporate leverage, or (iv) reduced corporate bond liquidity. While our findings are consistent with RPS increasing volatility for affected firms, it is important to rule out alternative explanations.

In Section 3.1 we examine firm earnings and find no evidence of a significant profitability decline following RPS implementation. Moreover, in Appendix A we show that electricity price increases cover the additional investments required by the RPS mandate. The fact that electricity price increases appear to achieve a full pass-through of the costs of RPS to consumers mitigates concerns that a drop in asset values is driving the observed credit spread widening. In Appendix B, we also present evidence that RPS did not significantly impact corporate leverage (Table B.1) or bond market liquidity (Table B.2), reinforcing the conclusion that higher yield spreads primarily reflect increased volatility.

4 Recovering Renewable Asset Price Volatility

We now combine our credit spread estimates with a no-arbitrage bond pricing model from Longstaff and Schwartz (1995) to impute the extra price volatility of renewable assets.[21]

4.1 No-arbitrage bond pricing

The value of a firm's assets (V) evolves according to a geometric Brownian motion:

$$dV = \mu V dt + \sigma V dZ_1, \tag{7}$$

where σ is a constant representing asset volatility, and Z_1 is a standard Wiener process.

The short-term riskless interest rate is defined by the following process:

$$dr = (\zeta - \beta r)dt + \eta dZ_2, \tag{8}$$

where ζ, β, and η are constants and Z_2 is another standard Wiener process.

We first construct the value of a hypothetical riskless discount bond, $D(r, T)$, with short-

[21]While recent models such as Chen (2010) emphasize the importance of explicitly incorporating business cycle factors, we choose to use the no-arbitrage model of Longstaff and Schwartz (1995) to recover asset volatility for a few reasons. First, it already does a reasonable job fitting some key data moments. Second, the RPS policy intervention ought to be orthogonal to business cycle fluctuations. Third, our inferences are transparent as a result.

term riskless interest rate r and maturity T following Vasicek (1977):

$$D(r,T) = \exp\left(A(T) - B(T)r\right), \tag{9}$$

where $A(T) = \left(\frac{\eta^2}{2\beta^2} - \frac{\alpha}{\beta}\right)T + \left(\frac{\eta^2}{\beta^3} - \frac{\alpha}{\beta^2}\right)\left(\exp\left(-\beta T\right) - 1\right) - \left(\frac{\eta^2}{4\beta^3}\right)\left(\exp\left(-2\beta T\right) - 1\right)$, $B(T) = \frac{1-\exp(-\beta T)}{\beta}$, and α is the sum of the parameter ζ, and a constant representing the market price of interest rate risk.

We then construct the value of a risky discount bond, $P(X, r, T)$, in the following way:

$$P(X, r, T, \sigma) = D(r,T) - \omega D(r,T)Q(X, r, T, \sigma), \tag{10}$$

where ω represents the proportion of the debt not recovered in the case of default, $Q(X, r, T, \sigma)$ is a measure of the cumulative default probability, and X represents the leverage ratio, which is defined as the ratio of firm value at issuance (V) to the lower bound value of the firm that triggers default ($\underline{V}$). This value, $\underline{V}$, is assumed to be constant and equal to the face value of debt. When $X = 1$, the firm defaults. We construct $Q(X, r, T, \sigma)$ using the same method as in Longstaff and Schwartz (1995).

To price coupon bonds, we simply construct a compound portfolio of risky discount bonds, each with a face value equal to the coupon rate, C. We do this by creating several bonds with increasing maturities and face value C, and then form a composite cash flow portfolio that covers the entire range of the maturity of the coupon bond, including the final face value payment. Formally:

$$P^c(C, X, r, T, \sigma) = P(X, r, T, \sigma) + C\sum_{j=1}^{TN} P\left(X, r, \frac{j}{N}, \sigma\right) \tag{11}$$

We select a value of N that is sufficiently large to approximate continuous time compounding, in our case 200. This gives us $P^c(C, X, r, T, \sigma)$. Then, we can calculate the yield-to-maturity that equates the present value of a coupon bond to its price as defined by $P^c(C, X, r, T, \sigma)$, and subtract this from the same object for a risk-free coupon bond equivalent to calculate the implied yield spread, $y(C, X, r, T, \sigma)$.

Impact of RPS. We incorporate the impact of RPS passage in our model as a change in the volatility of asset returns. If RPS passage were to increase this volatility as an expression of increased transition risk, this would lead to changes in the model implied yield spreads.

Suppose that ϑ represents the percentage change in volatility induced by RPS passage. Then our model would generate a difference in yield spreads (Δy) determined by the following

Table 6: Parameters

This table documents the parameters of our model. Values for the risk-free interest rate (r), the recovery rate, $(1-\omega)$, the coupon rate, C, and the leverage ratios for each ratings band ($\{X^{Aa},...,X^{B}\}$), are calculated using historical data. The volatility of firm assets, σ, and the RPS impact on volatility, λ, are calibrated using data moments. Details of the calibrated values for these parameters can be found in Table 7.

Parameter	Symbol	Source
Risk-free interest rate	r	Sample average from reduced form dataset (3.98%)
Debt not recovered after default	ω	0.7 (Longstaff and Schwartz (1995); Huang and Huang (2012))
Coupon Rate	C	Sample average from reduced form dataset (5.8%)
Leverage Ratios	$\{X^{Aa},...,X^{B}\}$	Calculated using data from Compustat
		$X^{Aa}=2.14$
		$X^{A}=2.23$
		$X^{Baa}=2.30$
		$X^{Ba}=1.80$
		$X^{B}=1.55$
Volatility	$\{\sigma^{Aa},...,\sigma^{B}\}$	Calibrated
RPS Implied Volatility Change	ϑ	Calibrated

expression:

$$\Delta y(\vartheta)=y(C,X,r,T,(1+\vartheta)\sigma)-y(C,X,r,T,\sigma) \tag{12}$$

It is simple to show that Δy is an increasing function in ϑ, and so the greater the increase in volatility, the larger the RPS impact on credit spreads.

4.2 Pricing model calibration

We calibrate our model using data in the post-RPS implementation period. We focus on moments in the data that allow us to calibrate the volatility parameter relevant to the RPS impact on credit spreads.

Parameters. We abstract away from interest rate risk by setting $\eta=0$ and $\beta=1$. Note that this also implies that ζ is equal to the fixed interest rate, r, and that the market price of interest rate risk is zero. The remaining parameters in the model are: the risk-free interest rate, r, the recovery rate, $(1-\omega)$, the coupon rate, C, the volatility of firm assets, σ, and the leverage ratio, X.

We use data values for r, $(1-\omega)$, C, and X. We use a risk-free interest rate (r) of 3.98%, which is the average yield of a 10-year treasury bond in the post-RPS sample period. For the recovery rate $(1-\omega)$, we use a value of $(1-0.7)$, which is within the typical range in the literature (Longstaff and Schwartz (1995); Huang and Huang (2012)). We set the coupon rate at 5.8%, which is the average coupon rate in our reduced form sample.

To account for variation in leverage ratios for different bonds, we calculate X for each rating band in our sample, using data from Compustat. We first construct the leverage ratio of all firms in the '4911' SIC code classification by taking the ratio of market value of equity plus total debt, to total debt. Using the variable names in Compustat, the firm-level leverage is defined as:

$$X_{i,t} = \frac{PRCC\_F_{i,t} \times CSHO_{i,t} + (DLC_{i,t} + DLTT_{i,t})}{DLC_{i,t} + DLTT_{i,t}}$$

where $PRCC\_F$ is the stock price at the close of the financial year, $CSHO$ is the number of common shares outstanding, DLC is total debt in current liabilities, and $DLTT$ is total long-term debt.

We then take the average of this measure within Moody's ratings bands. For ratings band $b \in B$, where B is the set of all ratings bands, the measure is defined as:

$$X^b = \frac{1}{|b|} \sum_{\kappa_{i,t}=b} X_{i,t}$$

where $\kappa_{i,t}$ is the average bond rating of firm i in year t. This process generates five distinct parameter values for X: $\{X^{Aa}, X^{A}, X^{Baa}, X^{Ba}, X^{B}\}$.[22] The values we calculate are 2.14, 2.23, 2.30, 1.80, and 1.55 respectively.

We directly calibrate the volatility parameter, σ, using the model. As with the leverage ratios (X), we do this at the ratings band level. This means we have five values of σ to calibrate, $\{\sigma^{Aa}, \sigma^{A}, \sigma^{Baa}, \sigma^{Ba}, \sigma^{B}\}$. Finally, we also calibrate the RPS impact on volatility, λ, that generates the difference in yield spreads for pre- and post-RPS data.

Moments. To calibrate our parameters, we target six moments. We use yield spreads, calculated for each of the five Moody's ratings bands, to identify our volatility (σ) parameters. We use our most conservative estimate of the impact of RPS on yields, around 69 bps, to identify the change in volatility, ϑ. For the yield spread, we use the post-RPS sample average of the yield at issue, minus the 10-year treasury bond yield, binned by ratings band.

To construct the model moment equivalent to the 69 bps estimate, we use a slightly modified procedure to the one outlined in Section 4.1. Given that we calibrate to post-RPS data, we identify λ by constructing counterfactual pre-RPS yields with volatilities scaled by $1/(1+\vartheta)$. We do this for each of the five ratings bands. We then subtract this value from the unadjusted yield spreads calculated using the original σ. Finally, we take the weighted average of these yield differences, weighting by the number of bonds in each rating band in our dataset. This gives us a model-based measure of Δy.

[22] While we have Aaa rated corporate bonds in our dataset, these are issued by private entities. As a consequence, we lack the necessary data to construct leverage ratios for the firms represented by these bonds. We therefore restrict our attention in this exercise to firms who are rated between Aa and B.

Table 7: Model Calibration Results

This table shows the calibrated parameters of our modified Longstaff and Schwartz (1995) model, described in Section 4.1. We calibrate the volatility (σ) using yield spreads, and the change in volatility implied by RPS (λ) using our most conservative reduced form estimate of the yield impact of RPS. We show the data moments we use to calibrate, and the implied model moments from our baseline case.

Panel A: Volatility

Ratings Band	σ	Data Yield Spread	Model Yield Spread
Aa	0.184	75bps	75bps
A	0.201	95bps	95bps
Baa	0.228	141bps	141bps
Ba	0.239	326bps	326bps
B	0.196	314bps	314bps

Panel B: Change in Volatility

Ratings Band	ϑ	Data Diff in Yield Spreads	Model Diff in Yield Spreads
All	0.195	69bps	69bps

Results. Our results can be found in Table 7. In Panel A we show, for each of the ratings bands, the calibrated value of the volatility parameter (σ), the data yield spread we aim to match, and the implied model yield spreads. We are able to generate a perfect match to the data. Taking a weighted average of the σ parameters, weighted by the number of bonds we observe in each ratings band, we find a post-RPS value of 0.212, or roughly 21%.

In Panel B we show the calibrated value of the change in volatility for pre- vs. post-RPS (ϑ), the observed and model-implied difference in average credit spreads in the pre- and post-RPS states. Again, we are able to match the data moment exactly with an imputed change in volatility (ϑ) of 19.5%. In actual terms, this implies that pre-RPS volatility was 0.177, or roughly 18%, and so RPS leads to an increase in volatility of roughly 3 percentage points.

Recovering renewable asset price volatility. Our firms subject to the RPS are being forced to use a mix of fossil fuels and renewables. To recover renewable asset pricing volatility, we take the post-RPS volatility measure of 21% (σ_{post}), and back out the underlying green volatility using the following expression:

$$(1-z)^2\sigma_B^2 + z^2\sigma_G^2 + 2z(1-z)\rho_{GB}^{firm}\sigma_B\sigma_G = \sigma_{post}^2 \tag{13}$$

where ρ_{GB}^{firm} is the correlation of shocks to the Green and Brown firm activities, $z = 0.318$ is the average post-RPS renewable energy proportion mandate, $\sigma_B = 0.18$, and $\sigma_{post} = 0.21$.

Using estimates from Hann et al. (2013), we assume that the within-firm correlation between the Green and Brown activities is 0.83.[23] This process gives us a Green activity volatility of $\sigma_G = 0.305$, which is roughly 70% greater than the volatility of Brown activities.

5 Implications for Decarbonization

We now show that the higher volatility of renewable assets has significant implications for equilibrium allocations to abatement capital. We consider a modified version of the elegant, continuous-time treatment of the two-sector, illiquid capital model of Eberly and Wang (2010). In our setting, we label the two sectors 'Brown' (B) and 'Green' (G) and modify the basic framework in Eberly and Wang (2010) to include climate disasters. We let the arrival rate of disasters be directly and inversely proportional to the stock of 'Green' capital, as in Hong et al. (2023b) and Nguyen et al. (2024).

5.1 Model setup

Output in both sectors is assumed to be $A_n K_n$, where K_n is the capital stock of sector n, which is proportional to production capacity in the data. A_n is the sector-specific productivity parameter, or output-to-capital ratio. Capital in each sector evolves continuously via a jump-diffusion process:

$$dK_n(t) = \Phi_n(I_n(t), K_n(t))dt + \sigma_n K_n(t)dW_n(t) - (1 - \Xi)K_n(t)dJ(t) \tag{14}$$

where $\Phi_n(I_n, K_n)$ captures how effectively investment goods are converted into installed capital, W_n is a Brownian motion specific to sector n, and J_t is a pure jump process with arrival rate $\lambda(K_G, K_B)$ that destroys a random proportion, $(1-\Xi)$, of capital in both sectors. As in Nguyen et al. (2024), we use the following simple functional form for $\lambda(K_G, K_B)$, where λ_G and λ_B are constant parameters that capture the arrival rate in the exclusively Green and Brown economies respectively:

$$\lambda(K_G, K_B) = \lambda_G + (\lambda_B - \lambda_G)\left(\frac{K_B}{K_G + K_B}\right) \tag{15}$$

[23] Hann et al. (2013) find that the median degree of within-firm, cross-segment cash flow and investment correlation is 0.911, with the mean being around 0.83.

We assume the following distribution for the proportion of capital retained post disaster, Ξ, taken from Pindyck and Wang (2013):

$$f_{\Xi}(\xi) = \beta \xi^{\beta-1} \tag{16}$$

As in Hayashi (1982), we assume that the adjustment technology in each sector is homogeneous of degree one in I and K, and takes the following functional form:

$$\Phi(I_n, K_n) = \phi_n(i_n) K_n = \left(i_n - \frac{1}{2}\theta i_n^2 - \delta \right) K_n \tag{17}$$

where i_n is the investment-to-capital ratio, θ is the common adjustment cost parameter, and δ is the common depreciation rate.

Households have Duffie and Epstein (1992) recursive utility and allocate their savings between a risk-free asset and the two risky sectors:

$$J_t = \mathbb{E}\left[\int_0^{\infty} f(C_s, J_s) ds \right] \tag{18}$$

$$f(C, J) = \frac{\alpha}{1-\psi^{-1}} \frac{C^{1-\psi^{-1}} - ((1-\gamma)J)^{\omega}}{((1-\gamma)J)^{\omega-1}} \tag{19}$$

All produced goods are either consumed or invested across the two sectors, so the goods-market clearing condition is given by:

$$C = Y_G + Y_B - I_G - I_B \tag{20}$$

5.2 Planner's Solution

Details of how we arrive at these solutions are provided in Appendix C. We guess and verify that the value function takes the following form:

$$J(K_G, K_B) = \frac{1}{1-\gamma} \left((K_G + K_B) N(z) \right)^{1-\gamma}$$

where $N(z)$ is the welfare measure, and $z = K_G/(K_G + K_B)$, the proportion of capital allocated to the Green sector. For the two-sector economy, sectoral investment-to-capital ratios are determined jointly by two implicit equations as functions of z:

$$\left(\frac{c^*(z)}{N(z)} \right)^{1/\psi} = \frac{\alpha}{\phi_B'(i_B^*(z))} \frac{1}{N(z) - zN'(z)} \tag{21}$$

$$\left(\frac{c^*(z)}{N(z)}\right)^{1/\psi} = \frac{\alpha}{\phi'_G(i^*_G(z))} \frac{1}{N(z) + (1-z)N'(z)} \tag{22}$$

where $c^*(z)$ is the optimal aggregate consumption-to-capital ratio. The following ODE also holds in the two-sector solution:

$$\begin{aligned}
0 = &\frac{\alpha}{1-\psi^{-1}} \left[\left(\frac{c^*(z)}{N(z)}\right)^{1-\psi^{-1}} - 1\right] + \phi_B(i^*_B(z))L_B(z) + \phi_G(i^*_G(z))L_G(z) \\
&- \frac{\gamma}{2}\left[\sigma_B^2 L_B(z)^2 + \sigma_G^2 L_G(z)^2\right. \\
&\left.+ 2\rho_{GB}\sigma_B\sigma_G L_B(z)L_G(z) + \frac{\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2}{2}M(z)\right. \\
&+ \frac{\lambda(z)}{\beta-\gamma+1}
\end{aligned} \tag{23}$$

where the functions $L_B(z)$, $L_G(z)$, and $M(z)$ are outlined in Appendix C.

Boundary conditions. Finally, the boundary conditions are given by the one-sector solution. Equilibrium investment rates in the one-sector case are given by the solutions to the following implicit non-linear expression:

$$A_n - i^*_n = \frac{1}{\phi'(i^*_n)}\left[\alpha + (\psi^{-1} - 1)\left(\phi'(i^*_n) - \frac{\gamma\sigma_n^2}{2} + \frac{\lambda_n}{\beta-\gamma+1}\right)\right] \tag{24}$$

Welfare, p_n, is given by:

$$p_n = (A_n - i^*_n)^{1/(1-\psi)}\left(\frac{\alpha}{\phi'_n(i^*_n)}\right)^{-\psi/(1-\psi)} \tag{25}$$

Hence,

$$N(0) = p_B, \text{ and } N(1) = p_G \tag{26}$$

As no analytical solution to the two-sector case exists, we solve this system, for a given set of parameters, using the finite differences numerical method to uncover the sectoral investment-to-capital ratios ($i^*_G(z)$, $i^*_B(z)$) and the welfare measure ($N(z)$) as functions of z.

Dynamics. Once we have the solution for optimal investment, we can then map out the stochastic process that governs z. This process includes both the endogenous decision-making processes of households, and also the exogenous stochastic processes that affect capital. We can represent the stochastic process of z by applying Itô's Lemma to the function

$f(K_G, K_B) = z = K_G/(K_G + K_B)$:

$$dz_t = \mu_z(z_t)dt + z_t(1-z_t)\sigma_G dW_G(t) - z_t(1-z_t)\sigma_B dW_B(t) \tag{27}$$

where the drift term is given by the following expression:

$$\mu(z) = z(1-z)\left(\phi_G(i_G^*(z)) - \phi_B(i_B^*(z)) + (1-z)\sigma_B^2 - z\sigma_G^2 - (1-2z)\rho_{GB}\sigma_G\sigma_B\right) \tag{28}$$

Note that there is no disaster jump term in the dynamics of z because disasters destroy the same proportion of Green and Brown Capital when they occur.

Tobin's q. As in Eberly and Wang (2010), Tobin's q is given by the following expression:

$$\begin{aligned} q_n(z) &= \frac{1}{\phi_n'(i_n^*(z))} \\ q(z) &= zq_G(z) + (1-z)q_B(z) \end{aligned} \tag{29}$$

Intuitively, the capital stock increases by $\phi'(i_n)$ per marginal unit of investment, and given that each unit of capital is valued at $q_n(z)$, it must therefore be the case that i_n is chosen to ensure that $\phi'(i_n)q_n(z)$ equals one.

Risk-free rate. We arrive at the equilibrium interest rate by first constructing the stochastic discount factor following the known result for Duffie-Epstein preferences given in Duffie and Epstein (1992). We then apply Itô's lemma to arrive at the following expression for the equilibrium interest rate:

$$\begin{aligned} r(z) = \alpha &+ \alpha\left(\frac{\psi^{-1}-\gamma}{1-\psi^{-1}}\right)\left[1-\left(\frac{c^*(z)}{N(z)}\right)^{1-\psi^{-1}}\right] + \gamma g(z) \\ &- (\gamma+1)\left[(1-z)\sigma_B^2 - z\sigma_G^2 - (1-2z)\rho_{GB}\sigma_B\sigma_G\right]\epsilon(z) - \epsilon(z)\left(\phi_G(i_G^*(z)) - \phi_B(i_B^*(z))\right) \\ &+ \frac{\psi^{-1}}{2}\left[\frac{d^2}{dz^2}\ln(c(z)) - (1-\gamma\psi)\frac{d^2}{dz^2}\ln(N(z))\right]z^2(1-z)^2\left(\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2\right) \\ &- \frac{(\gamma+1)\gamma}{2}\left(\sigma_B^2(1-z)^2 + \sigma_G^2 z^2 + 2\rho_{GB}\sigma_B\sigma_G z(1-z)\right) - \frac{\left(\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2\right)\epsilon^2(z)}{2} \\ &- \lambda(z)\frac{\psi^{-1}}{\beta-\psi^{-1}} \end{aligned} \tag{30}$$

where $\epsilon(z)$ and $g(z)$ are defined in Appendix C. The only term that differs between our expression for the equilibrium interest rate and the one in Eberly and Wang (2010) is the final term that accounts for the presence of disaster risks.

Table 8: Parameters

This table contains the values of our parameters from calibrating the model outlined in Section 5. We calibrate the adjustment cost parameter for the Green sector, θ, the Brown disaster arrival rate, λ_B, and the mitigation effectiveness of Green capital, $\tilde{\lambda}$. The remaining parameters are determined either from the literature, or using data on firms operating in the utilities sector.

Parameters	Symbol	Value
Time rate of preference	α	0.067
Elasticity of intertemporal substitution	ψ	2
Coefficient of relative risk aversion	γ	1.85
Productivity of Brown Sector	A_B	0.42
Productivity of Green Sector	A_G	0.29
Depreciation rate for K	δ	0.083
Adjustment cost parameter	θ	6
Diffusion volatility for K_B	σ_B	0.24
Diffusion volatility for K_G	σ_G	0.39
Correlation between shocks	ρ_{GB}	0.2
Green Disaster Arrival Rate	λ_G	0.05
Brown Disaster Arrival Rate	λ_B	1.50
Disaster Recovery Rate	β	39

Risk premium. We first derive the dynamics for the rate of return from investing in the Green and Brown sectors separately (μ_G^r and μ_B^r), then use the portfolio argument to arrive at the expected aggregate rate of return.

$$\mu_m(z) = \frac{1}{q(z)}\left[(1-z)q_B(z)\mu_B^r + zq_G\mu_G^r(z)\right] \tag{31}$$

The risk premium, $rp(z)$, is then the difference between $\mu_m(z)$ and $r(z)$. Details can be found in Appendix C.

5.3 Calibration

The model contains twelve structural parameters (see Table 8). Seven of them are fixed directly from data sources or well-established estimates in the literature; the remaining five are calibrated so that the stationary equilibrium replicates five empirical moments. To keep the exposition transparent, we first describe the externally assigned parameters, then set out the empirical moments, and finally explain how each of the five free parameters is pinned down.

5.3.1 Externally assigned parameters

Data Sample. Our calibration targets moments drawn from the period 1990–2004, which we treat as representative of a 'brown-only' economy—i.e., a time before meaningful penetration of renewable capital into the production sector. This assumption allows us to interpret the estimated parameters as reflecting the dynamics of the Brown sector in isolation. While Section 4 focused on utilities, our two-sector model is intended to represent the economy-wide capital stock. We therefore broaden our scope to include the goods-producing sectors where a coherent Green/Brown distinction can plausibly be made: Agriculture, Mining, Utilities, Manufacturing, and Transportation (NAICS 2-digit codes 11, 21, 22, 31–33, and 48). For these sectors, we collect data from the Bureau of Economic Analysis (BEA) and CRSP. The 1990–2004 window aligns closely with the pre-RPS period in most U.S. states, and it provides a clean empirical foundation for estimating Brown-sector fundamentals without contamination from large-scale green investment.

Productivity and Depreciation. To calibrate the output-to-capital ratio A_B and the depreciation rate δ, we draw on BEA data for the goods-producing NAICS industries listed above. We obtain current-dollar value added from *GDP-by-Industry Table 6.1A* and divide it by the current-cost net stock of private fixed assets from *Fixed Assets Table 3.1 ESI*, yielding an annual series for A_B. For depreciation, we take current-cost depreciation from *Table 3.4 ESI* and divide it by the same net capital stock to construct a time series for δ. In both cases, we take the median across years from 1990 to 2004. This procedure gives an average Brown output-to-capital ratio of $A_B = 0.42$ and a depreciation rate of $\delta = 0.083$, which we hold fixed in the model calibration. We assume that Green sector productivity is 70% that of Brown, i.e. $A_G = 0.29$, a value squarely within the empirical range implied by the literature.[24]

Return volatilities. We estimate Brown-sector return volatility, σ_B, using CRSP data from 1990 to 2004, again focusing on firms in the five goods-producing NAICS sectors. For each firm-year, we compute the standard deviation of monthly excess returns and annualize it by multiplying by $\sqrt{12}$. We then calculate the market-cap-weighted geometric mean of these firm-level volatilities within each year and take the median across years. This yields $\sigma_B = 24\%$. Because we treat the 1990–2004 period as effectively free of Green capital, this

[24]Leading macro–climate models typically embed a 30–45% productivity shortfall for clean capital. Acemoglu et al. (2012) initialize the quality of green inputs at 55% of dirty ones; Acemoglu et al. (2016) adopt a 60% ratio; and Hassler et al. (2012) back out an energy-saving TFP path that starts at 62% of energy-using TFP in 1970 and converges toward 80% by 2005. Setting $A_G = 0.70\, A_B$ therefore lies comfortably inside this 0.55–0.80 range.

estimate captures undiluted Brown-sector risk. To calibrate Green-sector volatility σ_G, we extrapolate on the finding in Section 4 and assume renewable assets are 70% more volatile than Brown ones, i.e. $\sigma_G = 39\%$. We think this is a reasonable baseline as intermittency, nascent technology risk or regulatory uncertainty also matter for green capital in other sectors. Finally, we set the cross-sector correlation $\rho = 0.2$, in line with empirical estimates of typical cross-sector correlations from Pollet and Wilson (2010).

Disaster technology. We follow Hong et al. (2023a) in setting the disaster arrival rate in a fully Green economy to $\lambda_G = 0.05$. For the distribution of capital losses conditional on a disaster, we adopt the beta distribution estimated by Dell et al. (2012), with shape parameter $\beta = 39$. This implies that, on average, a disaster destroys 2.5% of the capital stock. These values anchor the climate risk process in the model and allow us to study how the frequency and severity of disasters respond endogenously to the green share of capital.

5.3.2 Empirical moments

Five empirical moments are used to discipline the remaining parameters. First, we target an economy-wide Tobin's q of 2.5, an equity premium in the range of 6–7%, and a risk-free rate between 1–2%. We also match an aggregate investment-to-capital ratio of 10%, calculated using the same BEA sources and procedures used to estimate the output-to-capital ratio A and depreciation rate δ. Finally, we target an equilibrium Green capital share of 20%.[25]

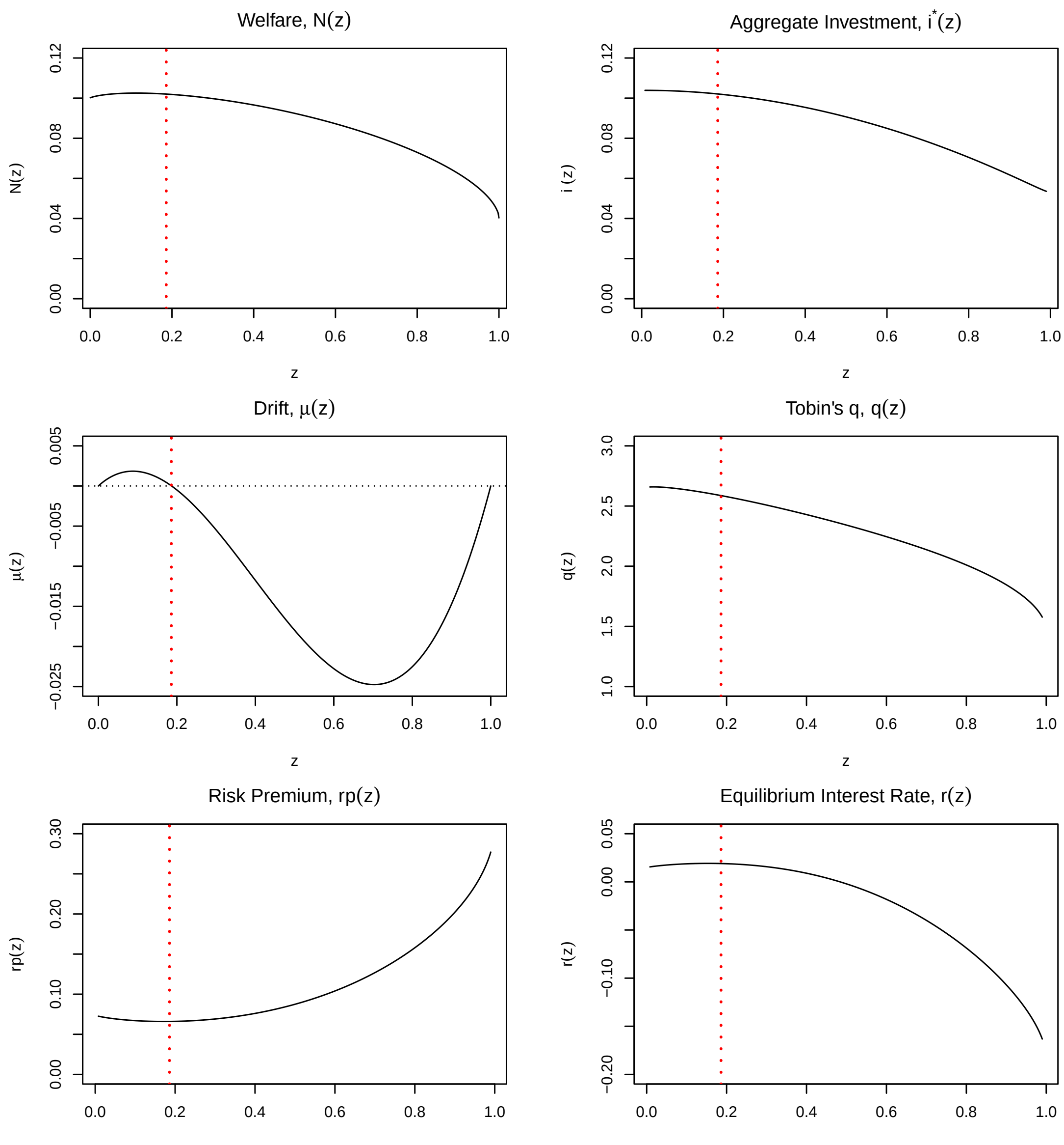
5.3.3 Calibrated Parameters

The Brown-sector disaster arrival rate λ_B is calibrated so that the stationary equilibrium reproduces the observed Green capital share of 20%, yielding $\lambda_B = 1.5$. The adjustment cost parameter θ, which governs both the level of investment and the shadow value of capital, is pinned down by jointly matching the investment-to-capital ratio and Tobin's q, resulting in $\theta = 6$. The preference parameters (α, ψ, γ) are calibrated simultaneously to match the risk-free rate, the equity premium, and—conditional on θ—the investment rate. This yields $\alpha = 0.067$, $\psi = 2$, and $\gamma = 1.85$. These values fall within standard ranges reported in micro-data studies of discounting (Samwick, 1998; Gustman and Steinmeier, 2005) and in macro-finance calibrations such as (Vissing-Jørgensen and Attanasio, 2003; Bansal and Yaron, 2004).

[25]This figure is consistent with sector-level estimates for goods-producing industries found in the London Stock Exchange Group's Investing in the Green Economy (2024) report.

Figure 3: Model Solution

In this figure we plot the equilbrium of the model in terms z, the proportional size of the Green sector. The top left panel shows the welfare function, $N(z)$, the top right shows the optimal aggregate investment, $i^*(z)$, the middle left shows the drift of the Green sector proportion, $\mu(z)$, middle right shows the aggregate Tobin's q, $q(z)$, the bottom left shows the aggregate risk premium, $rp(z)$, and the bottom right shows the equilibrium interest rate, $r(z)$. On all plots we indicate the interior solution of $z = 19\%$ by the vertical dotted lines. As the middle left panel makes clear, for any interior point on the $(0, 1)$ space, the drift of z ensures that the economy converges in expectation to the steady-state optimal proportion of $z = 19\%$.



5.4 Welfare, Investment, Asset Prices, and Proportion of Green Assets

The solution is outlined in Figure 3. In the top row, we show the welfare function, $N(z)$, and the aggregate investment function, $i^*(z)$, which are the solutions to the set of equations outlined in Section 5.2. In the middle row we show the drift of z, $\mu(z)$, and the aggregate Tobin's q, $q(z)$. In the bottom we show the risk premium, $rp(z)$, and the equilibrium interest rate, $r(z)$.

The higher volatility and lower productivity of the Green sector result in substantial asymmetry between the one-sector limit cases. The equilibrium of the dynamic model is illustrated by the drift panel: for any interior solution, the economy moves towards an equilibrium Green sector proportion of 19%. If z is below this critical value, then the economy drifts upwards towards the equilibrium, and vice versa for values of z above 19%. We include a vertical dotted line in all six plots to indicate this steady state solution. The aggregate investment rate is 10.2%, which is very close to the 10% we observe in the data. The aggregate Tobin's q is 2.59, which is also close to our target value of 2.5. The risk premium is 6.60%, and the equilibrium interest rate is 1.90%, which are within the target ranges of 6-7% and 1-2% respectively.

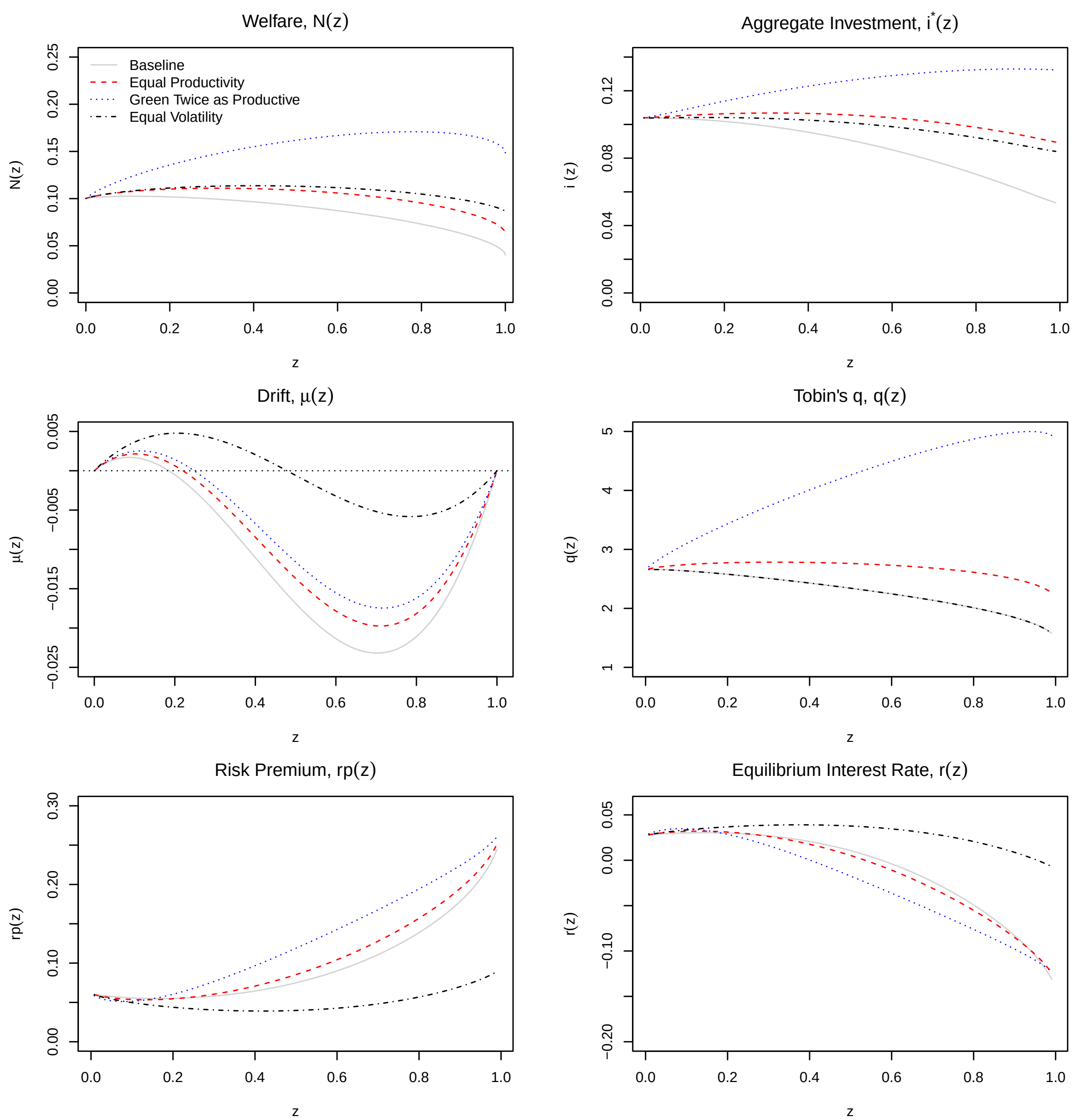
5.5 Counterfactual

To disentangle the forces driving the limited allocation to green capital, we conduct a series of counterfactual exercises that isolate the effects of first-moment (productivity) and second-moment (volatility) differences across technologies. While prior work has emphasized the lower average productivity of renewables, our framework allows us to quantify how much of the shortfall in green capital is instead driven by its elevated risk. We consider three cases. First, we eliminate the productivity gap by setting $A_G = A_B = 0.42$ (Equal Productivity). Since green technologies have become more efficient over time (Hassler et al. (2012)), one might expect that as this gap closes, the volatility channel will become less important; we therefore explicitly consider this scenario to assess how much of the green capital shortfall volatility alone can explain. Second, we grant green capital a substantial productivity edge by setting $A_G = 2A_B = 0.84$ (Green Twice as Productive). This more aggressive scenario serves as a stress test: if even dramatically higher productivity fails to close the gap, it would underscore the dominant role of volatility in limiting green investment. Third, we equalize volatility across sectors by setting $\sigma_G = \sigma_B = 0.24$ (Equal Volatility). In all cases, we hold preferences and all remaining parameters fixed at their calibrated baseline values.

Figure 4 displays the full model solution under each of these counterfactuals, alongside the

Figure 4: Counterfactuals – Model Solution

In this figure we plot the model solutions to three counterfactual cases. We show solutions for Equal Productivity ($A_G = A_B = 0.42$, dashed red line), Green Capital Twice as Productive as Brown ($A_G = 2 \times A_B = 0.84$, dotted blue line), and Equal Volatility ($\sigma_B = \sigma_G = 0.24$, dotted and dashed black line). We also include the baseline case (solid gray line).



baseline calibration. The effects are striking. Equalizing volatility alone more than doubles the equilibrium green capital share, from 19% to 48%. In contrast, removing the productivity disadvantage—despite being a natural focus in much of the climate policy literature—has a far smaller effect, increasing the green share to just 22%. Even granting green capital a dramatic twofold productivity advantage only raises the equilibrium share to 25%.

Figure 5 complements these findings by reporting the relative change in each of the five calibrated moments under the three counterfactuals. Unlike Figure 4, which plots the full model solution, this figure focuses solely on the *steady-state outcomes* implied by each case (i.e. when $\mu(z) = 0$). Presenting results this way sharpens the comparison across counterfactuals and makes clear which empirical targets are most sensitive to changes in model primitives. These patterns confirm that volatility, not productivity, is the dominant force shaping capital allocation in the model.

Why doesn't a large productivity advantage drive the green sector to dominance? We can get intuition from Equation (27), which we highlight again below

$$\mu(z) = z(1-z)\Big[\underbrace{\phi_G(i_G^*) - \phi_B(i_B^*)}_{\text{net productivity}} + \underbrace{(1-z)\sigma_B^2 - z\sigma_G^2 - (1-2z)\rho_{GB}\sigma_B\sigma_G}_{\text{diversification penalty}}\Big].$$

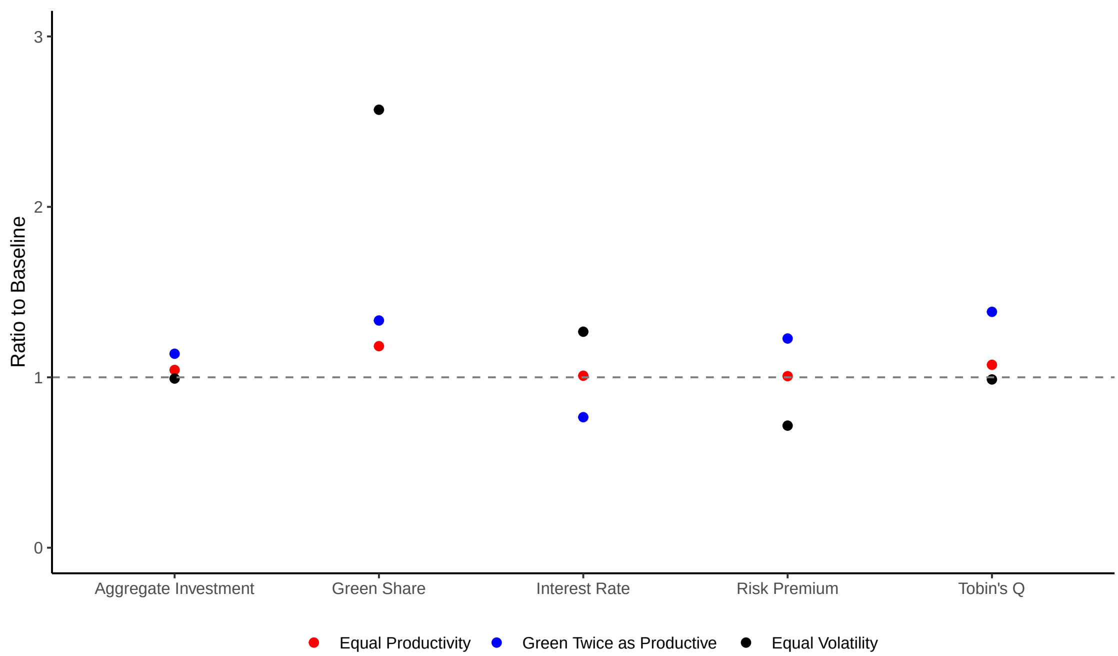
The first bracket is the net productivity edge after adjustment costs and depreciation.[26] Because $\phi(\cdot)$ is concave, its marginal effect diminishes quickly: every increase in A_G delivers progressively smaller gains in $\phi_G(i_G^*) - \phi_B(i_B^*)$, as enlarging the green sector means deploying investment in a region of steeper adjustment costs. The incremental gain in $\phi_G - \phi_B$ consequently flattens out. The second bracket is a *diversification penalty.* Its dependence on risk is strictly *linear* in the sectoral variances and covariance.

Equilibrium is reached when the two brackets exactly offset. Because the risk penalty grows linearly while the productivity reward grows at a diminishing rate, the penalty overtakes the reward well before z approaches half. Volatility thus delivers a constant marginal 'cost', whereas productivity delivers a shrinking marginal 'benefit', making second moment volatility —not first moment productivity —the decisive factor in fixing the steady-state green share. While both components matter, it is volatility that most constrains green investment, making it a central object for understanding the limits of decarbonization and for guiding climate finance policy.

[26] To see how this is the case, recall that $\phi_n(i) = i - \frac{1}{2}\theta i^2 - \delta$, so $\phi_n(i)$ is the *net* growth rate of capital in sector n: gross investment per unit of capital (i) minus quadratic adjustment costs and physical depreciation. Evaluated at the optimal policies $i_n^*(z)$, the difference $\phi_G(i_G^*) - \phi_B(i_B^*)$ is therefore the expected excess growth that a unit of green capital enjoys over a unit of brown capital *after* all installation frictions and wear-and-tear have been paid. It is this fully 'net' measure of sectoral performance that competes, in the drift of z, against the linear diversification penalty.

Figure 5: Counterfactuals– Moment Comparisons

In this figure we show how the five model-generated equilibrium moments (i.e. when $\mu(z) = 0$) used for calibration vary under the three counterfactual cases of: (i) Equal Productivity, (ii) Green Capital being Twice as Productive as Brown, and (iii) Equal Volatility across the Brown and Green Sectors. We express all counterfactuals as ratios to the baseline case.



6 Conclusion

We show that the price volatility of renewable assets is significantly higher than that of brown assets. We obtain our causal estimate by leveraging the response of electricity and credit markets to the implementation of RPS, which forced utilities to switch to renewables. This estimate is related to higher electricity price volatility and more volatile firm revenues, and is consistent with industry concerns about a host of uncertainties regarding renewables intermittency and policy implementation. We then examine the implications of higher green asset volatility for economy-wide decarbonization levels through the lens of a growth model in which the proportion of green and brown assets balances climate damages against diversification benefits for risk-averse households. A calibration to macro-financial moments suggests that higher green asset volatility is at least as important a determinant of decarbonization as the relative mean productivity of green versus brown capital.

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Appendix

A Cost Pass Through of RPS

RPS legislation requires that utility companies make costly investments in renewable capacity. As discussed in the introduction and in Section 3.1, developing new capacity involves both capacity and transmission investment, with the latter being particularly costly for renewable power sources (Andrade and Baldick (2017)). However, regulators can compensate producers for these costs by raising consumer electricity prices.

To assess whether price increases offset the costs associated with RPS, we conduct a difference-in-differences estimation design at the producer-year level. Our specification is a difference-in-differences design akin to the model described by Equation 3, where the dependent variable now takes one of three values: (i) the average annual consumer price in \$s per MWh of electricity, as measured by the EIA State Electricity Profiles data ($p^c_{q,s,t}$), (ii) the average level of transmission investment in dollars at the producer-type level divided by total MWhs, which we construct using firm-level observations in FERC Form 1 submissions ($I^{\$,Trans}_{q,s,t}$), and (iii) the average level of renewable capacity investment in dollars divided by total MWhs at the producer-type level, constructed using firm-level observations from the EIA (Form EIA-860) ($I^{\$,Renew}_{q,s,t}$).[27] As all three variables are represented as Dollars-per-MWh, we can assess how much of the investment costs are covered by any price increase effect.

Our findings are reported in Table A.1. We find that regulators fully compensate suppliers for the cost of investing in renewable energy by raising consumer electricity prices. Consumer prices increase by \$3.35 per MWh, while transmission investment increases by \$1.95 per MWh and renewable capacity investment by \$0.92 per MWh, for a total investment increase of \$2.87.

Our estimates suggest that transmission investment is particularly reactive to RPS passage, making up roughly 68% of the total investment burden. However, FERC data focuses on larger firms than the EIA data by construction, as utilities only appear in FERC if, for three consecutive years, they report at least 1 million MWh of total sales, 100MWh of annual sales for resale, 500MWh of annual power exchanges delivered, or 500MWh of annual wheeling for others (deliveries plus losses). In contrast, EIA data is collected when a plant's total generator capacity is 1 MW or greater and the generator, or the facility that contains the generator, is connected to the local or regional power grid with the ability to draw power from or deliver power to that grid. As a consequence, our estimate of the transmission effect may be slightly inflated by a sample that contains larger firms on average. Nonetheless, while 68% is on the high end of typical ratios for transmission vs. capacity costs, it is not outside the boundaries observed in the data.[28]

Finally, as well as capacity investments, utility providers can also meet RPS mandates through purchases of Renewable Energy Certificates (RECs). However, as these certificates do not involve any actual power purchasing, and are not reported separately in FERC Form 1

[27] To construct dollar values of capacity, we use the procedure outlined in Section 2.2.

[28] Andrade and Baldick (2017) report that in several cases transmission costs exceed fifty percent of the total power plant investment when constructing greenfield wind capacity.

Table A.1: Cost Accounting of RPS

This table presents results from several difference-in-differences estimation designs that offer a breakdown of the costs and compensation associated with RPS. In Column (1), we use the average price of the producer-type of suppliers at the annual level using the EIA State Electricity Profiles data. For Column (2), we use data on transmission capital from FERC Form 1 submissions at the firm-level, and then aggregate at the producer-type level. In Column (3) we use firm-level data from the EIA (Form EIA-860) on capacity in MWs, and transform this into a dollar value of capacity capital using the procedure outlined in Section 2.2. We scale all dependent variables by MWhs, such that all dependent variables are expressed in dollars per MWh.

Dependent Variables:	Electricity Price	Transmission Investment	Green Capacity Investment
Model:	(1)	(2)	(3)
Variables			
corp × post	3.350***	1.954*	0.9176**
	(1.227)	(1.007)	(0.3750)
Controls	Yes	Yes	Yes
Fixed-effects			
State-Year	Yes	Yes	Yes
Fit statistics			
Observations	398	450	310
R^2	0.98413	0.92074	0.52341
Within R^2	0.76599	0.20936	0.07986

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

submissions, we are unable to observe these purchases in the data, which makes it challenging for us to assess RPS impacts on REC purchasing.

B RPS Impact on Bond Issuance (Leverage) and Trades

As pointed out by studies in the empirical pricing of corporate bonds (Huang and Huang (2012), Collin-Dufresn et al. (2001)) following Merton (1974), there can be four potential explanations for why yield spreads of affected firms might have risen following the imposition of RPS: the mean asset value is reduced by RPS, the underlying volatility of the market value of assets went up, corporate leverage of the affected firms went up, or the liquidity of corporate bonds went down.

In Section 3.1, we rule out that the increase in yield spreads is driven by a drop in earnings. In this Section we confirm that neither leverage nor liquidity concerns explain the yield spread impact of RPS (Tables B.1 and B.2 respectively).

Bond Issuance. Using our debt issues data, we also test whether the size of the issue amount changes after passage of RPS. We use the same design as in the case of adjusted yields (Section 3.2.1), i.e. we estimate Equation 3 using the log of the issue amount as the dependent variable. We also conduct a state-by-state estimation. We include the same vector of fixed effects and controls as for adjusted yields, though we omit the log of issue amount as a control. Details can be found in Table B.1: in Column (1) we show results for the standard difference-in-differences estimation, and in Column (2) for the state-by-state design.

Trades of corporate and municipal bonds. With our lists of bond issues from corporate and municipal utilities, we gather data on the yearly frequency of trades of these bonds. For the trades of corporate bonds, we use information on the frequency and size of trades from Mergent FISD. For municipal bonds, we can track their trading using data from the Municipal Securities Rulemaking Board (MSRB). The MSRB provides information on the trades of all municipal bonds from 2005 to 2023. We can measure the number of trades each of our issues has each year over this sample period to examine whether the frequency of trades in these bonds changes after the introduction of a state RPS.

One problem with using these MSRB data for this approach is that several states passed their RPS plans around the beginning of the MSRB sample period. For those states, we do not have information on the number of trades of municipal issues before the RPS; therefore, we cannot measure whether the number of trades changed. So our analysis of the change in trading behavior will only include a subset of states where we have sufficient observations before and after the passage of the RPS.[29]

We construct annualized measures of bond trading at the producer-type level. We then estimate the specification outlined in Equation 3 using the absolute number of trades and

[29] The states we include in our analysis are Illinois, Kansas, Minnesota, Missouri, North Carolina, Ohio and Oregon.

Table B.1: Issue Amounts– Difference-in-Differences and State-by-State

This table presents results from difference-in-differences estimations that assess the impact of RPS on issue amounts post-RPS. In Column (1), we present the results from the baseline estimation design outlined in Equation 3, substituting the log of issue amounts for adjusted yields. In Column (2) we use a design that aggregates individual state-level regressions into a weighted average. We estimate Equation 4 using the log of issue amount as the dependent variable for each of the 14 states that passed RPS with a municipal exemption, and then aggregate using the precision of the estimates as weights. Standard errors are constructed at the state-year level for Column (1), and using the formula in Equation 5 for Column (2) (precision weighting). In all cases we control for the Moody's rating band, and the log of maturity of the issue.

Dependent Variables:	Log of Issue Amt.	
Model:	(1)	(2)
Variables		
corp × post	0.1047	-0.0584
	(0.4505)	(0.2156)
Controls	Yes	Yes
Fixed-effects		
State-Year	Yes	No
Year	No	Yes
Issuer	Yes	Yes
Security Type	Yes	Yes
Tax Code	Yes	Yes

Standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

the log number of trades as dependent variables. We control for a state-year fixed effect. Details can be found in Table B.2.

Table B.2: Bond Trade Difference-in-Differences

This table presents results from a difference-in-differences estimation design that examines the impact of RPS on the number of bond trades. In Panel A, we show summary statistics of our two measures of yearly bond trading frequency. In Panel B, we show the regression results.

Panel A: Variable	N	Mean	SD
Number of Trades of Corporates	47	4.04	2.52
Number of Trades of Municipals	45	16.28	39.00
Log Number of Trades of Corporates	47	1.51	0.48
Log Number of Trades of Municipals	45	1.95	1.11

Panel B: Dependent Variables:	Number of Trades	Log Number of Trades
Model:	(1)	(2)
Variables		
corp × post	-3.91	0.19
	(11.26)	(0.34)
Fixed-effects		
State-Year	Yes	Yes
Fit statistics		
Observations	92	92
R^2	0.80	0.63

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Two Sector Model Solution

C.1 Analytical Solutions

One Sector Case: Our solution to the one sector model closely follows the method in Pindyck and Wang (2013). Specifically, we arrive at Equations 24 and 25 by first outlining the Bellman equation for the social planner's problem:

$$0 = \max_C \{f(C, J) + \Phi_n(I_n, K_n)J'(K_n) + \frac{1}{2}\sigma_n^2 K_n^2 J''(K_n) + \lambda_n \mathbb{E}\left[J(\Xi K_n) - J(K_n)\right]\} \quad \text{(C.1)}$$

We take the first-order condition with respect to C, which given $C + I = Y$ gives us the following first-order condition with respect to I:

$$f_C(C, J) = \phi_n'(i_n)J'(K_n) \quad \text{(C.2)}$$

We then substitute the following conjectured value function into this first-order condition:

$$J(K_n) = \frac{1}{1-\gamma}(p_n K_n)^{1-\gamma} \quad \text{(C.3)}$$

With some manipulation, this gives us that:

$$c = \left(\frac{\alpha}{\phi_n'(i_n)}\right)^{\psi} p_n^{1-\psi} \tag{C.4}$$

Substituting this expression into the Bellman equation gives us Equation 24. Rearranging this expression in terms of p_n gives us Equation 25.

Two Sector Case: The solution method follows the approach of Eberly and Wang (2010). We first outline the Bellman equation:

$$\begin{aligned} 0 = \max_{I_G, I_B} \{ & f(C,J) + \phi_G(i_G)K_G J_G + \phi_B(i_B)K_B J_B + \rho_{GB}\sigma_G\sigma_B K_G K_B J_{GB} \\ & + \frac{1}{2}\sigma_G^2 K_G^2 J_{GG} + \frac{1}{2}\sigma_B^2 K_B^2 J_{BB} \\ & + \lambda(K_G, K_B)\mathbb{E}\left[J(\Xi K_G, \Xi K_B) - J(K_G, K_B)\right] \} \end{aligned} \tag{C.5}$$

Where $J = J(K_G, K_B)$ is the consumer's value function, and J_n is the derivative of that function with respect to K_n. We guess and verify that the value function takes the following form:

$$J(K_G, K_B) = \frac{1}{1-\gamma}\left((K_G + K_B)N(z)\right)^{1-\gamma} \tag{C.6}$$

Equations 21 and 22 are then simply the first order conditions of the above expression. We arrive at Equation 23 by substituting the two first order conditions, the conjectured value function, the function $\lambda(K_G, K_B)$, and the Duffie and Epstein (1992) utility functions into the Bellman equation, where the functions $L_B(z)$, $L_G(z)$, and $M(z)$ are defined as follows:

$$L_B(z) = (1-z)\left[1 - z\frac{N'(z)}{N(z)}\right] \tag{C.7}$$

$$L_G(z) = z\left[1 + (1-z)\frac{N'(z)}{N(z)}\right] \tag{C.8}$$

$$M(z) = \frac{z^2(1-z)^2 N''(z)}{N(z)} \tag{C.9}$$

Finally, the boundary conditions that pin down the function $N(z)$ are given by the solutions to the one-sector case, as discussed in the body of the paper.

$$N(0) = p_B, \text{ and } N(1) = p_G \tag{C.10}$$

Asset Pricing. We follow the same approach as in Eberly and Wang (2010). First, we let υ be the equilibrium stochastic discount factor. From Duffie and Epstein (1992) we know that:

$$\upsilon_t = \exp\left[\int_0^t f_J(C_s^*, J_s)ds\right] f_C(C_t^*, J_t) \tag{C.11}$$

As in Eberly and Wang (2010) we have that:

$$f_C(C_t^*, J_t) = \left(\frac{\alpha}{1-\psi^{-1}}\right)\left[\left(\psi^{-1}-\gamma\right)\left(\frac{c^*(z)}{N(z)}\right)^{1-\psi^{-1}} - (1-\gamma)\right] \tag{C.12}$$

$$f_J(C_t^*, J_t) = \frac{\alpha(C^*)^{-\psi^{-1}}}{((1-\gamma)J(K_G, K_B))^{\omega-1}} = \frac{\delta(N(z)(K_B+K_G))^{\psi^{-1}-\gamma}}{(C^*)^{\psi^{-1}}} \tag{C.13}$$

We then apply Itô's lemma to the stochastic discount factor and arrange terms to establish the drift of the process. This drift is then $-1/\upsilon$ of the equilibrium interest rate, z:

$$\begin{aligned}
r(z) = {} & \alpha + \alpha\left(\frac{\psi^{-1}-\gamma}{1-\psi^{-1}}\right)\left[1-\left(\frac{c^*(z)}{N(z)}\right)^{1-\psi^{-1}}\right] + \gamma g(z) \\
& - (\gamma+1)\left[(1-z)\sigma_B^2 - z\sigma_G^2 - (1-2z)\rho_{GB}\sigma_B\sigma_G\right]\epsilon(z) - \epsilon(z)\left(\phi_G(i_G^*(z)) - \phi_B(i_B^*(z))\right) \\
& + \frac{\psi^{-1}}{2}\left[\frac{d^2}{dz^2}\ln(c(z)) - (1-\gamma\psi)\frac{d^2}{dz^2}\ln(N(z))\right] z^2(1-z)^2\left(\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2\right) \qquad \text{(C.14)} \\
& - \frac{(\gamma+1)\gamma}{2}\left(\sigma_B^2(1-z)^2 + \sigma_G^2 z^2 + 2\rho_{GB}\sigma_B\sigma_G z(1-z)\right) - \frac{\left(\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2\right)\epsilon^2(z)}{2} \\
& - \lambda(z)\frac{\psi^{-1}}{\beta-\psi^{-1}}
\end{aligned}$$

where the functions $\epsilon(z)$ and $g(z)$ (the aggregate growth rate) are given by the following expressions:

$$\epsilon(z) = \psi^{-1}\left(-\frac{c'^*(z)}{c^*(z)} + (1-\gamma\psi)\frac{N'(z)}{N(z)}\right) z(1-z) \tag{C.15}$$

$$g(z) = (1-z)\phi_B(i_B^*(z)) + z\phi_G(i_G^*(z)) \tag{C.16}$$

To determine the risk premium, we follow the procedure in Eberly and Wang (2010) of first deriving the dynamics of investing in each sector by constructing $dR_n(t) = (D_n(t)dt + dV_n(t))/V_n(t)$ and then applying Itô's lemma. This gives an expected return in each sector of:

$$\begin{aligned}
\mu_B^r(z) = {} & dy_B(z) + \phi_B(i_B(z)) + z(1-z)\left[\phi_G(i_G(z)) - \phi_B(i_B(z))\right]\frac{q_B'(z)}{q_B(z)} \qquad \text{(C.17)} \\
& - z^2(1-z)(\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2)\left[\frac{q_B'(z)}{q_B(z)} - \frac{1}{2}\frac{q_B''(z)}{q_B(z)}(1-z)\right] + \lambda(z)\left(\mathbb{E}[\Xi^{1-\theta}] - 1\right)
\end{aligned}$$

$$\begin{aligned}
\mu_G^r(z) = {} & dy_G(z) + \phi_G(i_G(z)) + z(1-z)\left[\phi_G(i_G(z)) - \phi_B(i_B(z))\right]\frac{q_G'(z)}{q_G(z)} \qquad \text{(C.18)} \\
& + z^2(1-z)(\sigma_B^2 - 2\rho_{GB}\sigma_B\sigma_G + \sigma_G^2)\left[\frac{q_G'(z)}{q_G(z)} + \frac{1}{2}\frac{q_G''(z)}{q_G(z)}z\right] + \lambda(z)\left(\mathbb{E}[\Xi^{1-\theta}] - 1\right)
\end{aligned}$$

We then construct the expected return of the market portfolio as:

$$\mu^m(z) = \frac{1}{q(z)}\left[(1-z)q_B(z)\mu_B^r(z) + zq_G(z)\mu_G^r(z)\right] \tag{C.19}$$

The risk premium is then simply $\mu^m(z) - r(z)$.

C.2 Numerical Solutions

One Sector Case: We use a nonlinear equation solver to uncover the value of i_n^* that validates Equation 24 for a given parameter set, then calculate p_n using that value.

Two Sector Case: We have three unknown functions: $i_B^*(z)$, $i_G^*(z)$, and $N(z)$. We solve for these functions using the finite difference method. We construct a grid of values for z from 0 to 1, and then guess values for $i_B^*(z)$, $i_G^*(z)$, and $N(z)$ at every point on the grid. We enforce that $N(0) = p_B$ and $N(1) = p_b$. Using that guess, we apply a nonlinear equation solver for each grid point to find the exact solution.

Supplementary Appendix for Online Publication Only

The following supplementary tables and figures are for Hong, Kubik and Shore "Renewable Asset Price Volatility and Its Implications for Decarbonization".

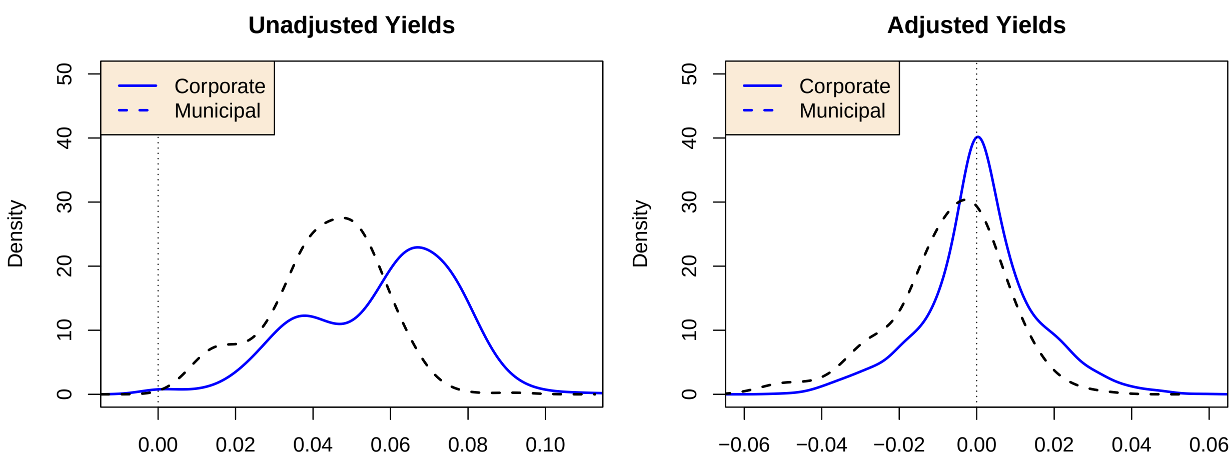
Table O.1: Summary of RPS Legislation in States without Exemptions

This table presents summary details of the passage of Renewable Portfolio Standards regulation in the 18 states that have thus far enacted the legislation without municipality exemptions. For the number of municipal and investor-owned producers, and the sales in gigawatt hours, we take the time series average.

State	Mandate Start	Maximum Green %	Year Max Achieved	No. Investor-Owned	No. Municipal	Investor-Owned Sales (gwhrs)	Municipal Sales (gwhrs)
California	2002	60	2030	7.55	13.15	150,028	60,649
Connecticut	1998	40	2030	1.7	1.65	29,681	21,986
District Columbia	2005	90	2041	0	0	4,121	0
Delaware	2005	21.5	2026	0	1.82	5,079	3,086
Maine	1999	84	2030	1.83	0	23,354	247
Maryland	2004	50	2030	0	1.6	31,447	6,426
Massachusetts	2002	100	2090	3.55	8.85	23,353	7,613
Michigan	2008	15	2021	8.75	18.05	84,254	11,472
Montana	2005	15	2015	2.1	0	6,734	3,989
Nevada	1997	50	2030	3.65	0	28,030	4,426
New Jersey	1999	52.5	2045	3.7	1	49,075	1,291
New York	2004	70	2030	9.25	4.25	58,142	24,567
Pennsylvania	2004	7.5	2020	7	1	83,452	5,312
Rhode Island	2004	100	2033	1	0	5,447	55
Texas	1999	5	2025	4.55	11.8	258,264	105,569
Vermont	2015	75	2032	2.2	4.75	4,299	1,269
Washington	2006	15	2020	3.95	3	29,476	52,003
Wisconsin	1999	10	2015	8	9.9	53,369	15,586

Figure O.1: Distributions of Adjusted Yields

This figure plots binned kernel density estimates of the distribution of the adjusted yields from municipal and investor-owned utilities, adjusted using a characteristic benchmark approach similar to Daniel et al. (1997). We construct benchmarks by forming 5x5x5 portfolios on Moody's rating, maturity, issue size, and yields. We then subtract the median yield in each portfolio from the actual value for each issue inside that portfolio.



O.1 RPS Impact on Earnings Volatility

Since earnings are tied to asset values under a discounted cash-flow framework, mean earnings or earnings volatility are reflective of the underlying mean assets or asset volatility, respectively.

Data on Producer financials. We collect data on operator-level financial fundamentals from the Federal Energy Regulatory Commission (FERC). This data is collected via mandatory 'Form 1' submissions from utility companies. This form consists of a comprehensive financial and operating report submitted annually. Our sample includes more investor-owned operators, and they generate higher earnings on average: 2,017 observations for investor-owned producers vs. 129 for municipal, with mean earnings of \$131.7m and \$9.3m respectively.[30]

Specification and Results. For the impact on net income (NI), we use the difference-in-differences design described in Equation 3 but at the firm level, including a firm fixed effect and controlling for the lag of log total assets. For earnings volatility, we use a cross-sectional measure, σ^{NI}, constructed by taking the standard deviation of the log change in earnings across all firms in the same producer-type across a given year. This is therefore a measure at the producer-type level, so we do not include any firm fixed effects in this regression. An important caveat is that earnings data is quite infrequent and sparse, and so we are not able to include any controls or additional fixed effects in this specification. Our results can be found in Table O.2. There is no significant negative impact of RPS on corporate to municipal earnings spreads (Column (1)). In Column (2), we observe a significant increase in the volatility of net income of investor-owned utilities in the post-RPS period.

[30] That we have more investor-owned utilities in the sample is unsurprising: as detailed by FERC, utilities are required by law to submit this form if at least one of the following criteria is met for three consecutive years prior to reporting: (i) 1 million MWh of total sales, (ii) 100MWh of annual sales for resale, (iii) 500MWh of annual power exchanges delivered, or (iv) 500MWh of annual wheeling for others (deliveries plus losses). Investor-owned operators are much larger on average, and so more likely to appear in the FERC data more frequently.

Table O.2: Firm Earnings and Earnings Volatility Difference-in-Differences

This table presents results from a difference-in-differences estimation design that examines the impact of RPS on firm earnings (net income, NI) and earnings volatility (σ^{NI}). In Column (1) we use firm-level data on net income as the dependent variable. In Column (2) we use a cross-sectional measure of earnings volatility as the dependent variable, constructed as the annual standard deviation of log changes in net income at the producer-type level (investor-owned or municipal).

Dependent Variables:	log(Net Income)	$\sigma^{\text{Net Income}}$
Model:	(1)	(2)
Variables		
corp		-0.3201**
		(0.1445)
corp × post	0.1970	0.9433**
	(0.4078)	(0.4313)
Controls	Yes	No
Fixed-effects		
State-Year	Yes	Yes
Firm	Yes	
Fit statistics		
Observations	1,843	331
R^2	0.71770	0.93114
Within R^2	0.00055	0.32057

Clustered (State-Year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*