Uncertainty of Stringency and Timing in US Climate Policy

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Abstract

Climate policy is far from certain in the United States. Major clean energy tax credits have experienced repeated cycles of short-term renewal and expiration, and the US government's environmental policies tend to be greatly affected by changes in the political affiliation of the administration. Given that, the investigation into the uncertainty of climate policy and its economic and environmental impacts in the US is paramount. I develop a dynamic stochastic model of the US economy with major carbon-emitting sectors, explicitly incorporating the uncertainty and varying stringency of the government's climate policies. The simulation results highlight that, in the face of policy uncertainty, the investment decisions can be preempted or delayed depending on the current policy stringency, and a deterministic model can over-predict CO_2 emissions, 8-12% more than when a stochastic model is used. The examination of policy timing scenarios reveals that achieving lower emissions in 2050 requires enacting stricter policies close to the target year whereas minimizing the cumulative emissions, thus contributing less to global warming, is accomplished by earlier adoption of policies, though possibly repealed later. The analysis further suggests that scenarios with earlier policy adoption

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are associated with up to 35% lower abatement costs than those with later policy adoption. Lastly, an extended model that considers learning-by-doing effects in cost reductions for low-emitting technologies leads to delayed abatement efforts, ending up with 1.3-1.7 times higher average abatement costs. The research would provide insights into climate policy analysis and have policy implications for the significance of stringency and timing of the climate policy adoption and pathways to meet the US mid-century climate goal and mitigate global climate change.

Keywords: US climate policy, climate policy uncertainty, dynamic stochastic model, abatement cost, policy timing, learning-by-doing

JEL Classification: Q58, Q54

1 Introduction

The Inflation Reduction Act of 2022 (IRA) is praised as a significant achievement in the history of US climate policy. Studies suggest that the IRA would help the US achieve net greenhouse gas (GHG) emissions 30-43% below 2005 levels in 2030, relative to 25-35% without it (Jenkins et al., 2022; Mahajan et al., 2022; Larsen et al., 2022). Among the drivers behind these expectations are two critical elements in the bill, each extending tax credits for clean energy projects and clean vehicle purchases through 2032[1]. Without the IRA, they were scheduled to phase out or down soon, possibly ending up decelerating the momentum in the deployment of renewable energy and electric vehicles. This ten-year-long extension is unprecedented as investment and production tax credits (ITC and PTC) have been characterized with repeated short-term expiration and renewal cycles. For example, the wind energy PTC extended over 10 times since its initial enactment in 1992 (Sherlock, 2020). Many of the policies to incentivize low-carbon technologies, including clean energy, had expiration dates, faced significant policy uncertainty, and eventually incurred occasional policy lapses, from two days to 11 months, and consequent boom-bust cycles of in-

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[1]See *Section 13101, 13102, 13103, 13701,* and *13702* for clean electricity credits, and *Section 13401, 13402,* and *13403* for clean vehicle credits
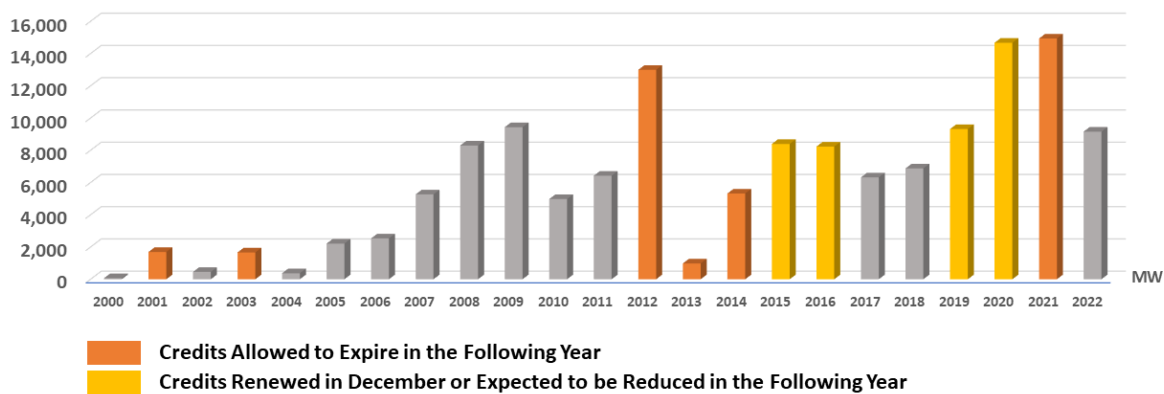
Figure 1: Annual Wind Power Capacity Additions (MW) and Policy Renewal and Expiration

vestment[2](Stokes and Breetz, 2018). Figure 1 shows the bunching of investment in wind power before expected policy expiration, particularly in 2001, 2003, 2012, and 2021. Thus, despite the decade-long guarantee of tax credits, it may be still uncertain whether the Act will accomplish up to its target[3], and furthermore, whether the US economy will actually reach carbon neutrality by the mid-century, due to the uncertainty surrounding the government's commitment to climate policy. A political pendulum of energy and environmental policy in the US has swung throughout its history (Ruckelshaus, 1996). The trend has continued to this date, especially, in the arena of the climate policy, which was illustrated by a series of the US government's decisions of withdrawal from and reentry to the Paris Agreement.[4] The changes in the government's political affiliation in the US have tended to end up with weakening or repeal of environmental legislation. Given that, the investigation into the uncertainty of climate policy and its economic and environmental

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[2]In retrospect, the wind and solar tax credits have never expired as their renewal retroactively applied to the producer (Sherlock, 2020). Still, failure to extend before their expiration dates results in considerable uncertainty for investors.

[3]After the passage of the IRA, there have already been few Republican-led attempts to repeal climate provisions of the IRA, including "H.R. 812 - Inflation Reduction Act of 2023" introduced by Rep. Andy Ogles (R-Tenn.) and debt ceiling proposal in 2023. Furthermore, some of 2024 republican presidential candidates, including Trump, may plan to tighten the budgets for the IRA tax credits (See https://www.politico.com/news/2023/08/16/how-a-republican-president-could-hobble-the-climate-law-00111555 for details).

[4]See https://www.nytimes.com/interactive/2020/climate/trump-environment-rollbacks-list.html and https://www.npr.org/sections/inauguration-day-live-updates/2021/01/20/958854421/biden-to-move-quickly-on-climate-change-reversing-trump-rollbacks for how a following administration attempted to undo what its preceding one does on environmental policies.

impacts in the US is paramount.

Previous US models that examine climate policies tend to focus on the economic impacts of climate change policies, including carbon pricing and revenue recycling schemes (Goulder and Hafstead, 2017; Yuan et al., 2019), using general equilibrium approaches. A recent study that analyzes the economic implications of the IRA uses a simplified neoclassical growth model with a focus on the electricity sector to evaluate the macroeconomic impacts of the IRA tax credits and compare them with those of carbon pricing (Bistline et al., 2023). Despite their thorough modeling of the economy and policy instruments, they rarely discuss the uncertainty and feasibility of the climate policy adoption and only model the implementation of alternative climate policies at a certain point in time or for a particular period. Theirs might be naive approaches considering the US political volatility and the fact that a carbon price has never been introduced at a national level and is not supported by the majority in the US (Rabe, 2018).[5] The political feasibility and timing of policy action are relevant and critical in economic assessments of climate policies, and frameworks that can incorporate differentiated political feasibility assumptions are necessary (Goulder, 2020). Fried et al. (2021) attempt to analyze the effects of the uncertainty around climate policy adoption on the US economy by comparing two pre-tax steady states with and without the risk of a carbon tax using a dynamic general equilibrium model. However, their representation of the policy risk, as a one-time event with a probability, is far simpler than the evolution of climate politics in the real world, and the study is not designed to show the possible future pathways of the economic and environmental outcomes.

Climate policy uncertainty has been discussed more in the literature that is based on real options theory (Dixit and Pindyck, 1994), mostly with a conceptual model of a specific sector. Real options approach to an investment decision analysis takes into account the value of holding an option to invest and waiting for new information that reduces uncertainty. Fuss et al. (2008) investigate the impacts of market price volatility and climate change policy uncertainty on the diffusion of

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[5]Even in Washington State, a relatively liberal state, two carbon tax referendums in 2016 and 2018 failed to win the majority, and it is predicted that the Washington's Pigouvian tax is unlikely passed in other states as well (Anderson et al., 2019).

mitigation technologies in the electricity generation sector. The policy uncertainty is specified as bifurcation scenarios with a set of (non)commitment year and commitment probability. They find market uncertainty leads to an earlier action whereas policy uncertainty induces a delay of investment in carbon capture and storage technologies. Their conceptual analysis is intuitive in providing the different impacts of distinct types of uncertainties. However, it is limited in the technology investment options and its specification of policy uncertainty might be less realistic.

A more realistic characterization of climate policy uncertainty adopted in real options framework might be a jump process with a frequency (Fuss et al., 2009; Reinelt and Keith, 2007; Blyth et al., 2007). When compared with a more frequently changing Brownian motion type CO_2 price, a less often updated policy regime is found to be preferred by investors and also by policy-makers who aim to reduce cumulative CO_2 emissions (Fuss et al., 2009). Also, by showing a shorter time window of policy change can deter investments, increasing policy certainty is emphasized (Blyth et al., 2007). In a similar context, Prest et al. (2021), by examining energy investments under uncertainty, highlight durable, even if modest, policies can induce investment in green energy as these policies serve as a signal to stricter carbon price, given their preferred uncertainty specification. Those studies are significant in that they explain the relationship between policy uncertainty and investment in low-emitting technologies and provide perspectives on policy certainty. Still, their studies are based on simplified single-sector model with only few technology options and thus fall short of a complete analysis of impacts of policy uncertainty on the entire economy.

The present study aims to investigate the impacts of US climate policy uncertainty on its economy and to show differing pathways by 2050 given policy uncertainty. The primary focus lies in the results of investment patterns, electricity generation by technology type, electric vehicle miles traveled (eVMT), and CO_2 emissions and abatement costs. The suggested model explicitly incorporates the possibility of switches of the government's commitment to its climate policies. The US economy is characterized by a neoclassical growth model with the primary energy, electricity generation, transportation, and final goods sectors. The primary energy sectors include coal, natural gas, and crude oil. For the electricity generation sector, the model considers four types of power

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plants: coal, natural gas, solar, and wind power plants. Transportation service is provided by either gasoline-based internal combustion engine cars or electric vehicles. The research investigates how climate policy instruments, which imitate the IRA bill's tax credits, and their implementation timing would impact the supply of electricity and transportation, specifically, the substitution between non-renewable energy and renewable energy and between gasoline and electric vehicles, and thus CO_2 emissions from those sectors. Policy uncertainty is represented as a Markov process, where the next period's policy state is dependent on the current policy state and a corresponding transition probability. It is assumed that the stringency of climate policy is decided in each presidential election year, and is put into effect after a year lag of implementation. Different levels of stringency are associated with different levels of tax credits for emissions reduction technology options in energy and transportation sectors. Lastly, the research adds to the basic model learning-by-doing (LBD) effects in capital investment cost reduction to analyze the interaction between LBD and policy uncertainty.

To solve this non-stationary dynamic stochastic model, the study adopts the Simulated Certainty Equivalent Approximation method (Cai and Judd, 2023). This method is developed to solve a large-scale dynamic stochastic model with non-stationarity and potential kinks, which have been thorny issues to conventional approaches, including value function iteration, as they undergo a process of function approximation. By utilizing optimal control method and certainty equivalent approximation, the method is shown to solve a non-stationary dynamic stochastic model in environmental and resource economics in a more stable and efficient manner (Steinbuks et al., 2023).

The main analyses are fourfold. In the first analysis, I examine the general impact of accounting for stochasticity in a climate change policy analysis, comparing economic and environmental outcomes from a deterministic model and its stochastic variant. The second analysis investigates a political economic aspects of policy uncertainty with a particular form of policy transition specification. Third analysis discusses the timing uncertainty of policy implementation and contrasts distinct scenarios characterized with the equal length of periods, yet with varied schedules of an identical set of policies. The last analysis extends the basic model to incorporate learning-by-doing

effects in technology capital investment costs to explore the interaction between policy uncertainty and endogenous technological growth and how it impacts economic and environmental outcomes.

To summarize the results, the first analysis finds that accounting for the stochasticity of the climate policy regime in the model can overall lead to a wider range of outcome pathways, in terms of renewable electricity generation and electric vehicles miles traveled, relative to using a deterministic model with perfect-foresight assumption. These trends are attributable to investment decisions delayed or preempted due to the policy uncertainty. When currently in a stringent policy state, it is optimal to invest in low-emitting technology to exploit tax credits today, whereas investment is held up when in a lenient policy state. Interestingly, all representative sample paths discussed in the first analysis demonstrate lower CO_2 emissions, up to 12% (around 243 million metric tons) when simulated using the stochastic model. The trend is driven differentially by the bunching of investment in stricter policy scenarios or by reduced and delayed investment in the electricity and transportation sectors in laxer policy scenarios. In terms of abatement costs, the stochastic model estimates the average costs 2.5 times higher than the deterministic model does. The efficiency of mitigation efforts are lower under uncertainty due to the ill-timed investment decisions under uncertainty.

The second analysis provides a political economic aspect of modeling uncertainty. The analysis adopts policy uncertainty specification based on persistent policy assumption and demonstrates the results closer to those from the deterministic model. In the most stringent policy scenario, the results with policy persistence exhibits 28.5% lower renewable electricity investment through 2050 and also a narrower range of outcomes than the results from the original volatile policy specification. The abatement costs from this analysis is estimated to range between the original stochastic model results and the deterministic model results. The results suggest the role of policy durability in improving the efficiency of mitigation efforts.

In the third analysis of policy implementation timing uncertainty, the results imply that scenarios with policy adoption concentrated in the later periods bring about outcomes with more renewable electricity generation and lower CO2 emissions in the year 2050. On the other hand,

scenarios with policies enacted in the earlier years see less CO2 emission cumulatively through 2050. In terms of abatement costs, earlier policy adoption scenarios, despite later policy drop, out-perform later adoption scenarios, achieving a maximum of 35% average abatement cost reduction. Lastly, frequent switches in policy regimes would cause more boom-bust cycles in investment, ending up with higher spending on subsidies and an average abatement cost that is 30% higher than earlier adoption scenario.

The last analysis illustrates that the extended model with learning-by-doing effects generally projects lower annual emissions in 2050, yet higher cumulative emissions through 2050. When learning-by-doing effects interact with policy uncertainty, investments accelerate in the later periods thanks to increased capital returns, and more emissions reductions are induced close to the mid-century. Due to this later transition to lower-emitting technologies, the model estimates 1.3-1.7 times higher average abatement costs within the simulation period, relative to the basic model with exogenous technological growth. The analysis stresses the significance of model specification choices in a policy analysis with fast-growing technologies.

This research contributes to the literature on the economic analysis of US climate policy and decarbonization pathways, where a deterministic model is often used. The suggested model explic-itly incorporates the possibility of switches of the government's commitment to climate policies, setting it apart from the literature (Goulder and Hafstead, 2017; Yuan et al., 2019; Bistline et al., 2023) which assumes perfect foresight and adopts scenario-specific parameters to address future uncertainty. In addition, the model analyzes the effects of policy uncertainty throughout the entire US economy, different from previous studies using real options approaches which focuses only on the electricity sector (Fuss et al., 2008; Reinelt and Keith, 2007; Blyth et al., 2007; Prest et al., 2021). Furthermore, incorporating endogenous technological growth and examining its interaction with policy uncertainty is another innovation, often absent in real options-based literature on cli-mate policy uncertainty. In the context of investment under uncertainty, the study is distinct from the previous literature in that whether the action of investment is committed earlier or delayed is not always clear, and rather depends on the current policy state and the expected policy state. An-

other potential significance of the study relates to its consideration of policy schedule uncertainty and political economic aspects in a policy analysis. This is particularly important for a country like the US, which occasionally observes a swinging political pendulum and whose environmental policies are politically polarized. In this aspect, policy uncertainty may only be partially resolved for a certain period of time before a significant event such as the presidential election takes place, unlike the literature specifying uncertainty that can be resolved completely once new information arrives (Fried et al., 2021). The results of this research would help inform policy-making by addressing various aspects of US climate policy, underscoring the significance of considering policy uncertainty in a policy analysis and highlighting the differences in the efficiency and effectiveness of climate policies across scenarios.

2   Data and Calibration

Data are used as reference for model parameter calibration or as inputs for model simulation. For calibration, the US gross domestic product (GDP), capital stock, electricity generation and capacity by energy source, fossil fuel extraction and consumption are used. The US gross domestic product and capital stock are based on the data from the Bureau of Economic Analysis (BEA). The data on fossil fuel extraction, electricity generation, and transportation sectors come from the US Energy Information Administration (EIA). Next, simulation requires projections of capital investment costs for the period of interest. An EIA's Annual Energy Outlook (AEO) provides estimated projections of overnight capital investment costs of power plant by technology type and light-duty sales prices for various scenarios. I adopt the projection of reference case of the AEO 2022. To compute the electricity generation and gasoline vehicle CO_2 emissions in the simulation, I calculated future carbon emissions intensity by dividing the CO_2 emissions by sectoral production. Lastly, population projection is drawn from the US Census Bureau. Some of projections are provided until 2050, and thus the inputs for the rest of the simulation periods are extrapolated. The base year values are included in Appendix A.

2.1 Calibration

A comprehensive set of parameters are calibrated to match the reference EIA projections: social time preference, discounting factors, sectoral depreciation rates, productivity parameters, fossil fuel extraction cost parameters, elasticity of substitution and cost share parameters in production functions. The calibration results are included in Appendix B.

3 Method

3.1 Model

This study proposes a stochastic growth model to examine the impacts of climate policy uncertainty on the US economy. A social planner's problem incorporating electricity generation, resource extraction, and transportation sectors, shown in Figure 2, is solved using the Simulated Certainty Equivalent (SCEQ) method (Cai and Judd, 2023) for 2023 through 2050. The dynamic paths of optimal investment and production are determined to maximize the social welfare in the face of policy uncertainty. All model equations are presented in Appendix D.

3.1.1 Economic Structure and Policy Impacts

The US economy is specified with focus on the sectors which play a major role in the CO_2 emissions and thus often subject to the target of a climate policy. For simplicity, I assume a closed economy where the domestic demand is entirely met by the domestic supply. Though this may be a plausible assumption for the net total energy trade as the US observed a switch from a net importer to a net exporter in recent years. Still, the supply of particular products, including crude oil, are dependent on imports and thus their trade need to be accounted, which can be a caveat of the study.

Figure 2 shows the economic structure adopted for the study. There is a final output produced using four inputs–capital, labor, energy and transportation. The representative household allocates

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the output to consumption, investment, or extraction of fossil fuels. The energy input is comprised of electricity and primary fossil fuels. The electricity is generated from five different types of power plants – coal, natural gas, solar PV, wind, and the others. The electricity supply from the others is exogenously given and assumed to be constant. The primary fossil fuels include coal, natural gas and crude oil. The transportation sector only considers the miles traveled by gasoline- or electricity-powered light duty vehicles that account for 70-80% of vehicle miles driven in the US, and other light-duty vehicles, including diesel and hybrid, are not modeled in the current study. Medium- and heavy-duty trucks are assumed to be aggregated into general capital stock as they are mostly used for industrial transportation.

The CO_2 emissions accounted for in the study include emissions from the electricity generation sector and and light-duty vehicles, which together constitutes around 50% of gross CO_2 emissions in the US. Modeling the rest of CO_2 emissions and potential impacts of relevant policy schemes is beyond the scope of this study.

As shown in Figure 2, the focus of analysis lies in the impacts of climate policy uncertainty on the investment and production decisions made in the electricity generation, resource extraction and transportation, and the consequential influence on CO_2 emissions. For example, the following equation that describes the law of motion for the renewable energy capacity explains how a tax credit impacts the decisions:

$$K_{t+1}^s = \left(1 - \delta^{nf}\right) K_t^s + \frac{I_t^s}{\left(1 - \tau_t^{renew}(X_t)\right) p_t^s} \tag{1}$$

where K_t is the generation capacity, δ^{nf} is the capital depreciation rate for renewable energy capacity, and p_t^s is the overnight capital costs per Watt installation. τ_t^{renew} is the investment tax credit for solar and wind power plants and is a function of the policy state, X_t. Depending on a realized tax credit, $\tau_t^{renew}(X_t)$ (e.g., 30%), in a given year, per unit investment cost can either decrease or increase, thus contributing to the changes in the returns on investment and investment decisions. A similar process applies to the investment in electric vehicle stocks, as shown in the
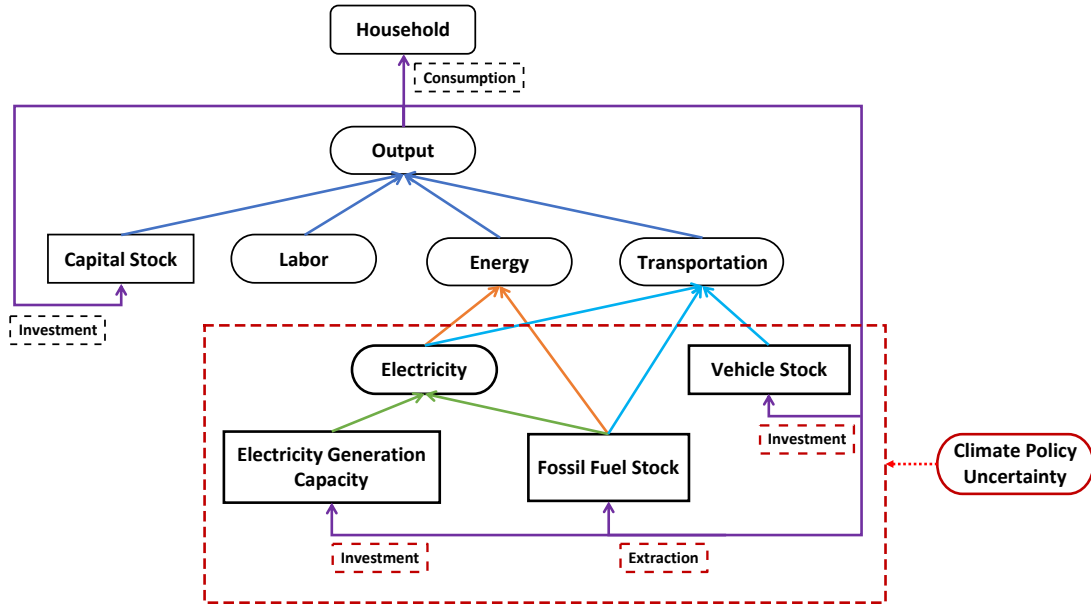
Figure 2: Economic Structure Schematic Diagram

equation 13. The following section explains the policy state transition mechanism.

3.1.2 Policy Uncertainty Module

The study considers two types of tax credits that draw on the recently-passed Inflation Reduction Act of 2022. The IRA extended the current production tax credit (PTC) for wind energy (*Sec. 13101*) and investment tax credit (ITC) for solar energy (*Sec. 13102*) until 2024 and introduced new clean electricity credits for both wind and solar effective from 2025 (*Sec. 13701* and *13702*)[6]. Also, a purchase of a clean vehicle qualifies for up to $7,500 tax credit under Internal Revenue Code Section 30D (*Sec. 13403*). Each tax credit is expected to incentivize the installation of renewable power plants and purchase of electric cars. As most tax credits in the IRA, I assume there is no cap on tax credit distribution.

In simulating, it is assumed that the IRA is effective until 2024 under certainty thanks to the

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[6]To simplify modeling, the PTC for wind is replaced with the ITC in simulations. Though this change is not consistent with the existing legislation, there was a precedent when taxpayers can choose to receive ITC instead of PTC for wind energy under the American Recovery and Reinvestment Act of 2009 (P.L. 111-5).

two years of extension, and after then the uncertainty is introduced. With the incentive level of the IRA indexed as the policy state, $X_t = 1$, three other policy states are specified in proportion to IRA: $X_t =$ 0, 1/3, and 2/3 represent zero policy state, one third of IRA, and two thirds of IRA, respectively. For example, for the policy state equal to 1/3, the clean energy ITC is 10%. The rationale behind the highest state equal 1 is based on the historical ITC maximum, and as new technologies threaten incumbents, more controversies and opposition tend to arise against the technologies (Stokes and Breetz, 2018).

The policy uncertainty is characterized as a Markov process with four possible policy states, $X_t \in \left\{0, \frac{1}{3}, \frac{2}{3}, 1\right\}$, and the time-varying transition probability matrix in year t,

$$
\mathbf{P}_t = \begin{pmatrix}
0.4 & 0.35 & 0.25 & \\
0.25 & 0.4 & 0.25 & 0.1 \\
0.1 & 0.25 & 0.4 & 0.25 \\
& 0.25 & 0.35 & 0.4
\end{pmatrix} \qquad \textit{for } t = \textit{election years}
$$

$$
\mathbf{P}_t = \begin{pmatrix}
1 & & & \\
& 1 & & \\
& & 1 & \\
& & & 1
\end{pmatrix} \qquad \textit{otherwise}
$$

The matrix above shows the probabilities of transition from the current state (row, i) to the next state (column, j). For example, the probability of switching from the most stringent state of $X_t = 1$ to the second most stringent one, $X_{t+1} = \frac{2}{3}$, is 0.35, shown in $P_{t,4,3}$ for election years. The realization of a policy shock every four years, in presidential election years, determines the stringency of climate policy, X_t. For every policy state, there is 40% chance of no policy change in the next presidential term, and a transition to an adjacent level specified as more probable than a move to a farther state in an attempt to model the existence of policy stickiness. It is assumed that the policy state changes with a year lag after the presidential election year considering law

implementation process. Under this future climate policy uncertainty, investment and resource extraction decisions are optimized through 2050.

This study considers a policy regime change as an exogenous factor. The probability distribution of adoption or repeal of a climate policy is not known and, thus, the policy state changes can fall into the category of ambiguity or deep uncertainty[7]. When the parameter values are ambiguous, the most common measure to address this is sensitivity analysis (Cai, 2021). I conduct sensitivity analyses with respect to the transition probability in Appendix E to examine how the solutions change and whether they are qualitatively robust.

3.1.3 Learning-by-Doing Effects (Extended Model)

An extended model considers learning-by-doing (LBD) effects in capital cost reductions. The basic model takes the EIA baseline projections of capital costs, p_t^s, for all sectors, whereas the extended model formulates capital costs as functions of cumulative capital additions, $K_t^{s,cumulative}$, for a sector, s (Arrow, 1962):

$$p_t^s = a^s \cdot \left(\frac{K_t^{s,cumulative}}{K_0^{s,cumulative}} \right)^{b^s} + c^s \tag{2}$$

where $a^s + c^s = p_1^s$ (the initial year cost). b^s represents the learning rate parameter for the sector s. Adding the second constant term imply the existence of a lower bound for capital cost. The LBD effects are incorporated in four relatively fast-advancing sectors–natural gas, solar, and wind power plants, and electric vehicle–and coal power plant and gasoline vehicle cost projections still follow the EIA baseline projections.

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[7]A growing body of the literature in economics relates extreme weather events to voting behaviors and the public support for climate policy (Liao and Junco, 2022; Elliott et al., 2023; Sisco and Weber, 2022; Holub and Schundeln, 2022). Still, in political science, societies have been slow in politically accepting climate change and proclimate policy is lobbied against by interest groups (Colgan and Hinthorn, 2023).

4   Results

In this section, four main analyses are presented based on the dynamic stochastic model simulations. First, the overall effects of modeling policy uncertainty is examined by comparing results from deterministic and stochastic versions of the basic model. The outcomes of interest include electricity generation by technology, vehicle miles traveled by vehicle type, CO_2 emissions, and emissions abatement costs. This analysis would highlight how optimal decisions in technology investments are made differently under uncertainty and their consequent impacts on the economic and environmental outcomes. The second analysis examines the effects of policy persistence. By adopting a particular specification of Markov transition matrix, the analysis would give a glimpse of how a political economic element can be incorporated in the current research. Thirdly, the effects of policy implementation timing are investigated by comparing scenarios with the same length of policy execution periods, yet differentiated by their implementation schedules. It aims to show, as with policy stringency equal, how policy enforcement timing can drive varied outcomes and abatement costs in a dynamic setting. In the last section, the model is extended by adding learning-by-doing effects in electricity and transportation technology investment costs. The comparison between the basic model and the extended model with endogenous technological growth highlights the differences between the two modeling approaches when interacting with policy uncertainty.

4.1   Effects of Uncertainty

In Figures 3-6, four outcomes from the deterministic model and the stochastic model simulations are displayed. For each figure, the left panel shows four deterministic model results that correspond to each of the four possible policy state stringency from zero to one. The right panel shows the range of all sample paths of stochastic model simulations, together with the sample paths of the policy scenarios identical with those simulated in the deterministic setting. The sample paths are generated from 1000 simulation runs. Despite their policy state paths equal, the stochastic

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model is distinct from the deterministic model in that it incorporates policy state uncertainty into optimization process unlike the deterministic one that assumes all policy state is known at the beginning with certainty based on perfect foresight assumption. The uncertainty comes in from the 2024 election, whose impact goes into effect from the year 2025.

First, all outcomes exhibit distinct pathways between the deterministic and stochastic model results. The deterministic model simulations generate smooth paths of outcomes whereas the stochastic model runs produce spike shape and piecewise shape of pathways for investment and low-emitting technology outputs, respectively, even when the policy state stays constant throughout all periods. This illustrates how optimal investments are determined differently under certainty and under uncertainty, and the necessity of stochastic modeling for an analysis of policy implementation uncertainty as underscored in Goulder (2020).

In Figure 3, renewable electricity investment patterns in stochastic model simulations shows the boom-bust patterns, similar to the patterns found before tax credit expiration for wind energy in 2013 (Figure 1). When the current policy regime is more stringent, as in the US today, and provides generous credits and reduced or zero credits are expected tomorrow, which includes the cases of "*Stochastic: Policy=1*" or "*Stochastic: Policy=2/3*", investment decisions are made before the potential switch in the regime and a bunching of investment happens. On the contrary, in the scenarios of "*Stochastic: Policy=1/3*" or "*Stochastic: Policy=0*", classified as relatively lenient policy scenarios, investment is delayed until the next policy state realization, waiting for higher tax credits tomorrow. This is a type of results commonly found in real options literature (Fuss et al., 2008) as well as manifested in the real world[8]. When comparing the net present value of cumulative investment of deterministic and stochastic model results, it is found that for two laxer scenarios, stochastic results show lower investment (31% for *Policy=0* and 17% for *Policy=1/3*), whereas for two stricter scenarios, stochastic results show higher investment (46% for *Policy=1* and 5% for *Policy=2/3*). This implies that, as in the current case of the US with a 30% tax credit, when a signal of policy uncertainty and expectation of lower tax credits go into the market, there

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[8]In 2014, wind tax credit was absent before it is renewed in December and a large quantity of wind power capacity was added in December.

could happen a bunching behavior and, thus, more government expenses than estimated using a deterministic model. On the other hand, if the US falls into a state with lower tax credits and there exists a debate in the Congress over increasing tax credits, investment into lower-emitting technologies might be delayed and substantially lower, slowing the transition toward a low-carbon economy.

These investment pattern differences lead to gaps in renewable electricity generation and electric vehicle miles traveled, though the latter is less obvious. As shown in Figure 4, the two relatively stricter scenarios result in higher renewable electricity under uncertainty (11% for *Policy=1* and 3% for *Policy=2/3* in 2050), and in the other scenarios, lower renewable electricity under uncertainty (8% for *Policy=0* and 3.5% for *Policy=1/3* in 2050). The consequences of differential economic decisions across the scenarios, interestingly, generate similar trends in total CO_2 emissions. All four sample scenarios show lower emissions from stochastic model results, yet via different channels. Lower CO_2 emissions under in the stringent scenarios are attributed to expedited investment in low-emitting technologies due to the exploitation of the currently higher tax credits. On the other hand, in the less strict scenarios, the main driver is the reduced and delayed investment across the economy, including fossil fuel power capacity, with the expectation of higher tax credits for renewables and electric vehicles. As a result, in 2050, stochastic model projects 12% lower emissions for *policy=1* and 8% lower for *policy=0*. This implies that using a deterministic model to evaluate the impacts of proclimate policies may over-predict greenhouse gas emissions, thus allocating subsidies higher than required to meet a target.

Lastly, the effects of uncertainty is also revealed in the difference in abatement costs between the two types of the model. Abatement costs associated with tax credits can be estimated by dividing the present value of total costs over time, which include both private investment and public tax credits, by cumulative emissions reductions with respect to the scenario without a tax
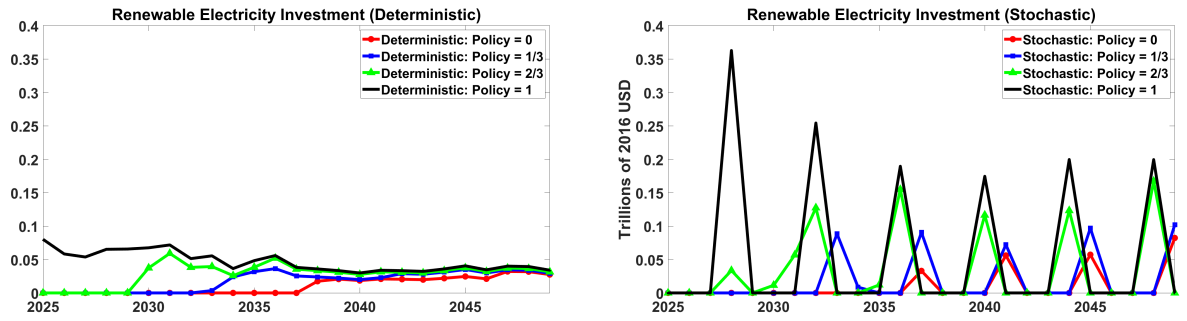
Figure 3: Renewable Electricity Investment
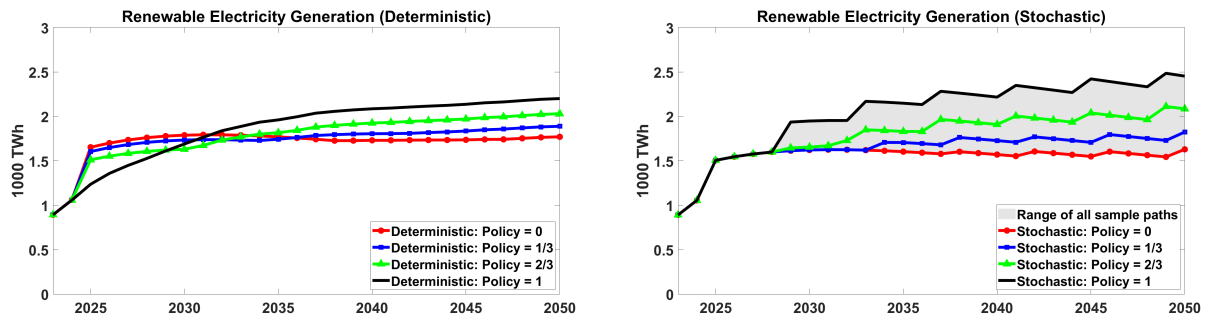
Figure 4: Renewable Electricity Generation
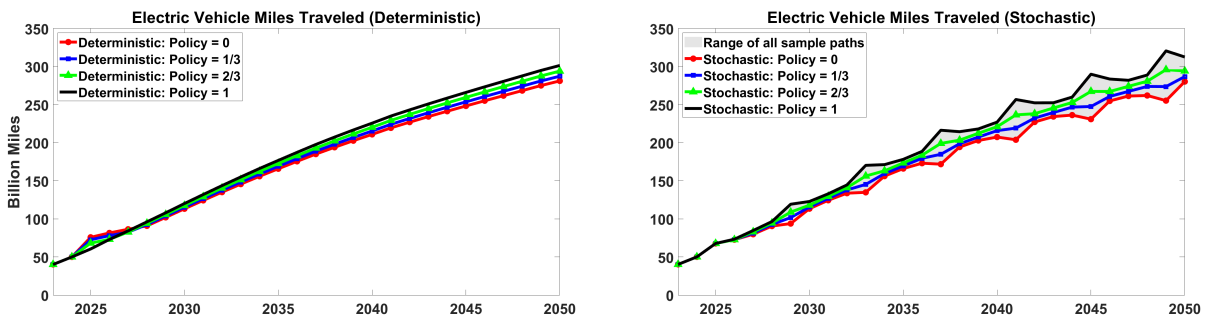
Figure 5: Electric Vehicle Miles Traveled
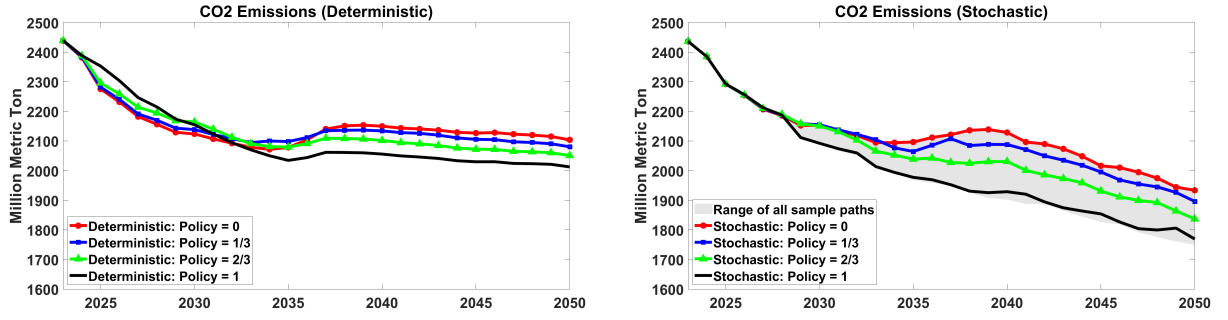
Figure 6: CO_2 Emissions

credit (*Policy=0* scenario in the current study). In a study that estimated emissions abatement costs related to IRA tax credits using a dynamic deterministic model, the cost for the power sector is estimated to be \$45-61 per metric ton of CO_2 (Bistline et al., 2023)[9].

When the abatement costs for electricity sector in Table 1 are compared with the previous literature, the stochastic model estimates are three to four times higher and the deterministic model estimates are relatively closer. The first and foremost difference with Bistline et al. (2023) is the computation. They considered total investment made during ten years of IRA implementation and estimated the benefits of the expenses for 30 years (10 years of policy implementation plus the following 20 years). In contrast, in this study, the benefit period coincides with the policy-effective period that is between 2022 and 2050. When using the same approach adopted in this paper, their estimate can increase to \$140-190, much closer to the stochastic model results. However, it should be noted that there is model component difference as well.

In general, the stochastic model exhibits higher abatement costs. In the *Policy=1* scenario, the stochastic model result shows 2.5 times higher than the deterministic one. The substantial difference might be attributable to inefficient investment decisions made under uncertainty. Abatement cost is determined by the total emissions reduced and the total money spent. These determinants are related to two critical factors: electricity sector total factor productivity and overnight capital costs. In the basic model, they are assumed to follow exogenous paths based on the EIA baseline

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[9]Other previous literature estimated a similar range of the abatement costs associated with tax credits: \$33-50 per metric ton (Greenstone et al., 2022) and \$35 per metric ton (Stock and Stuart, 2021).

Table 1: Electricity Sector Average Abatement Costs (between 2022-2050)

	Deterministic (USD / Metric Ton)	Stochastic (USD / Metric Ton)
Policy=1/3	-3.6226	179.99
Policy=2/3	40.57	179.65
Policy=1	87.392	215.64

projections. Under certainty, the decisions can be optimized in a way that the return on capital investment is maximized given those exogenous inputs. However, under uncertainty, the investment decisions are made in a preemptive manner with a bunching or reduced and delayed. Thus, this ill-timed investment, driven by policy uncertainty, not by economic efficiency, would lead to increased abatement costs.

4.2 Effects of Policy Persistence

The previous section focuses mainly on the discussion of policy uncertainty as a modeling component. This section provides a political economic aspect of modeling uncertainty, as the policy state transition matrix can change depending on a political economic view. In Section 4.1, the model is simulated with policy uncertainty characterized with an assumption that the policy regime is to a certain degree volatile. However, this assumption might be far from realistic. It is argued that reversing policy can be costly (Thrower, 2018) and there has been growing supporters and coalitions supporting the deployment of renewable energy (Zysman and Huberty, 2013). On the other hand, as new technologies become mature and threaten their incumbents, subsidy policy can face opposition (Stokes and Breetz, 2018). Prest et al. (2021) attempts to incorporate this political economic view in their carbon price analysis. They assume a strongly persistent carbon price. Their Markov transition matrix of a carbon price is constructed in a way that although it takes a long time to implement a carbon price, once a high carbon price is achieved, it remains forever.

In this study, I flip their approach to apply it to the study's "carrot" type of policies. An alternative transition matrix implies highly sticky tax credits, although zero tax credits are inevitable in
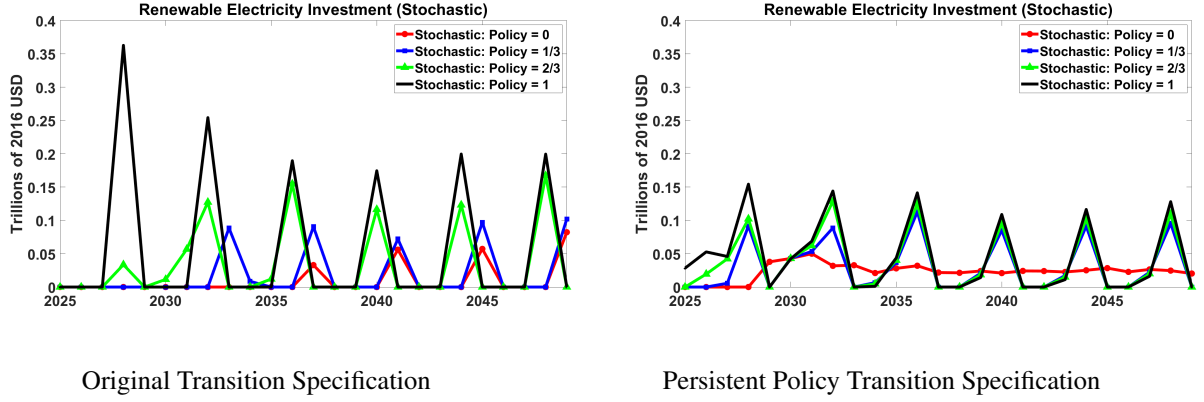
Figure 7: Renewable Electricity Investment Comparison

the long term:

$$\mathbf{P}_t = \begin{pmatrix} 1 & & & \\ 0.10 & 0.90 & & \\ & 0.10 & 0.90 & \\ & & 0.10 & 0.90 \end{pmatrix} \qquad for\ t = election\ years$$

As shown in Table 7, the results from the original specification are associated with larger variations across scenarios than those from alternative persistence specification. As the persistence policy assumption guarantees a high probability of maintaining the current state, the results follow a similar pattern of those from the deterministic model. Consequently, the distribution of outcomes is narrower, as found in the deterministic model results. Compared to the stochastic model results in the previous section, the new specification results show renewable electricity investment is 28.5% lower, renewable electricity generation in 2050 is 10% lower, and annual CO_2 emissions in 2050 is 2.6% higher for the *policy=1* scenario (Figures 7-9).

Similar to the deterministic model results of Table 1, the abatement costs are estimated rela-
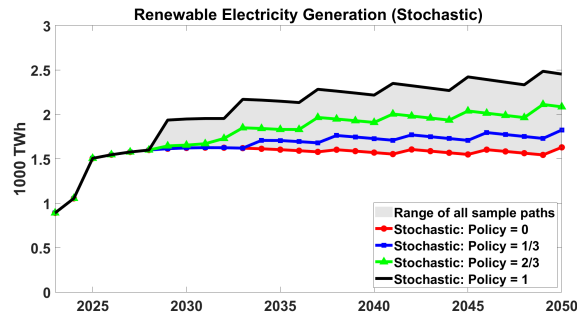
21
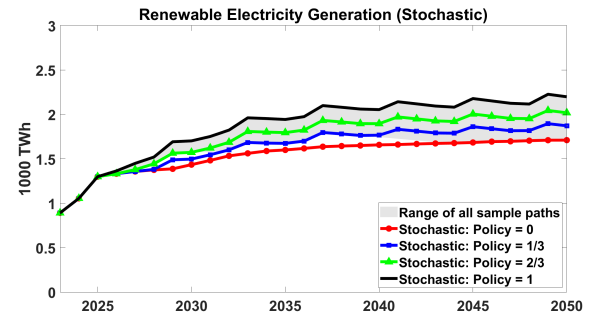
Original Transition Specification   Persistent Policy Transition Specification

Figure 8: Renewable Electricity Generation Comparison
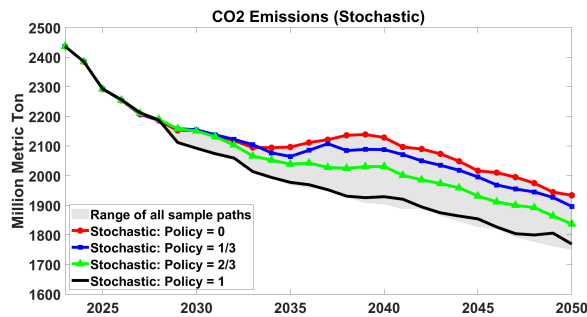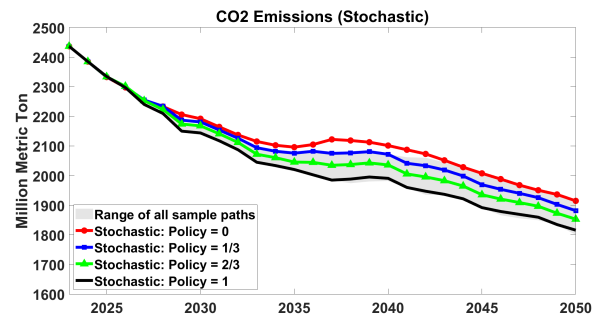
Original Transition Specification   Persistent Policy Transition Specification

Figure 9: CO_2 Emissions Comparison

Table 2: Electricity Sector Average Abatement Costs (between 2022-2050)

	Original (USD / Metric Ton)	Persistent Policy (USD / Metric Ton)
Policy=1/3	179.99	168.62*
Policy=2/3	179.65	179.58
Policy=1	215.64	195.69

*This scenario is not realizable with the persistence specification setting

tively lower for the model with policy stickiness than with policy volatility (Table 2). This might imply that durable policy can contribute to more efficient allocation of resources, preventing ill-timed investment bunching or delaying.

4.3 Effects of Timing

This section investigates the impacts of policy implementation timing under uncertainty. Specifically, four representative sample scenarios are compared. Those scenarios are characterized with the equal number of policy effective years, but with varied schedules of implementation. The IRA policy state, $X_t = 1$, is used as a test policy state except for the first scenario, (1) *Constant 2/3*, where the policy is consistently $X_t = \frac{2}{3}$. This scenario is presented as a reference to analyze whether a scenario consistent in providing a lower incentive, $X_t = \frac{2}{3}$, can be as effective as a frequently-shifting scenario with a higher incentive, $X_t = 1$. Next, in the (2) *Frequent Switch* scenario, the policy state switches between zero and one every election year. (3) *Earlier Adoption* and (4) *Later Adoption* scenarios have the IRA policy state in place for the same number of periods (i.e. 12 years after 2025) as the (2) *Frequent Switch* scenario. However, two scenarios are distinct in terms of when the policy is maintained and abandoned (effective in earlier or later 12 years). All policy scenarios are plotted in Figure 10.
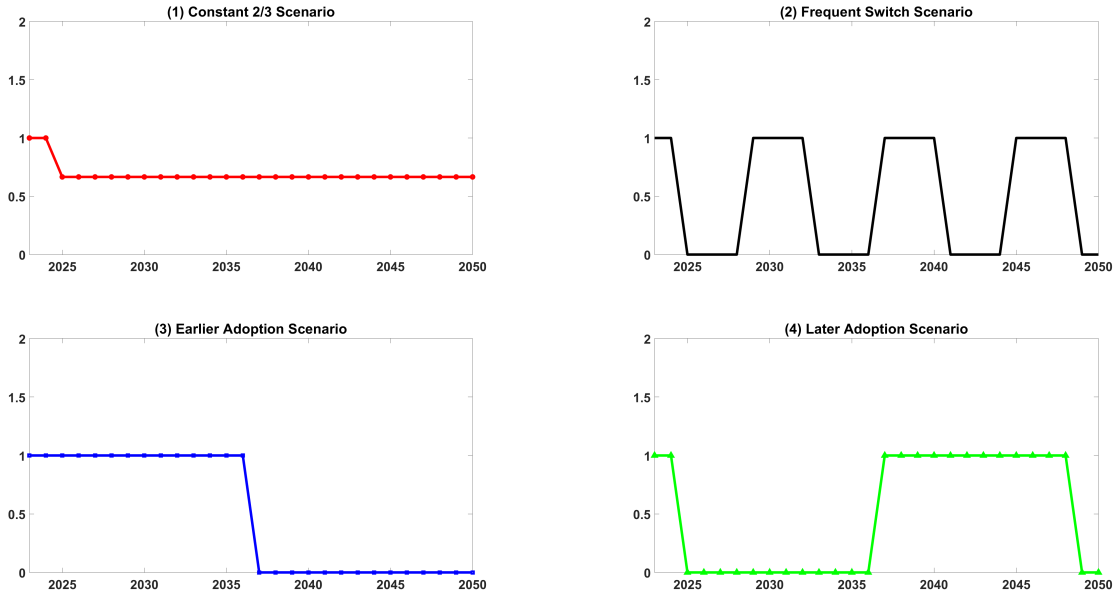
Figure 10: Policy Scenario Paths

Figures 11-12 and Tables 3-4 exhibit the results of the four aforementioned scenarios. Scenarios with the policy effective in the later periods (i.e., (2) *Frequent Switch* and (4) *Later Adoption*), in general, are associated with lower annual CO_2 emissions and higher accumulated capital in low emitting technologies around the mid-century. This would be mainly because after an early implementation of the policy, if it is not maintained until renewables and EV become as competitive as their conventional counterparts, the early investment depreciates with time and they are replaced with conventional higher emitting technologies. This trend is found in (3) *Earlier Adoption* where natural gas power plant capacity increases, reducing renewable share, in later periods absent of a policy.

One notable outcome is that the annual CO_2 emissions in 2050 and the cumulative CO_2 emissions throughout the entire simulation period show only slight difference. Though scenario (2) *Frequent Switch* indicates the lowest emissions in 2050, the value is only 2.6% and 3.8% lower than (1) *Constant 2/3* and (3) *Earlier Adoption*. In a cumulative perspective, (3) *Earlier Adoption* exhibits the lowest emissions, but it is only 2.5% and 3.1% lower than (4) *Later Adoption* and (1) *Constant 2/3*. Lastly, despite the small discrepancies, it can be said that meeting the mid-century

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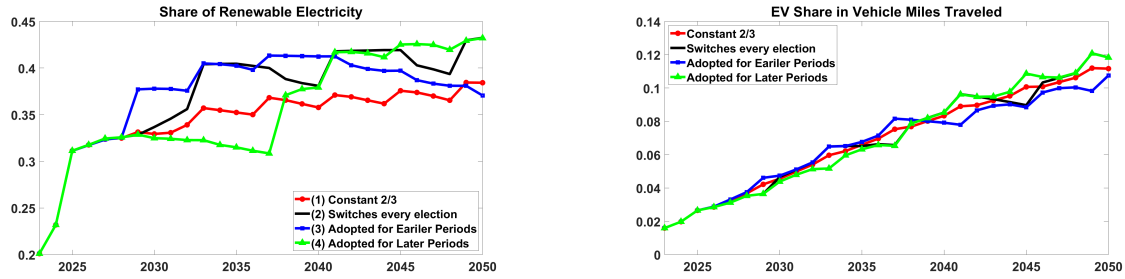
Figure 11: Shares of Renewable Electricity Generation and Electric Vehicle Miles Traveled
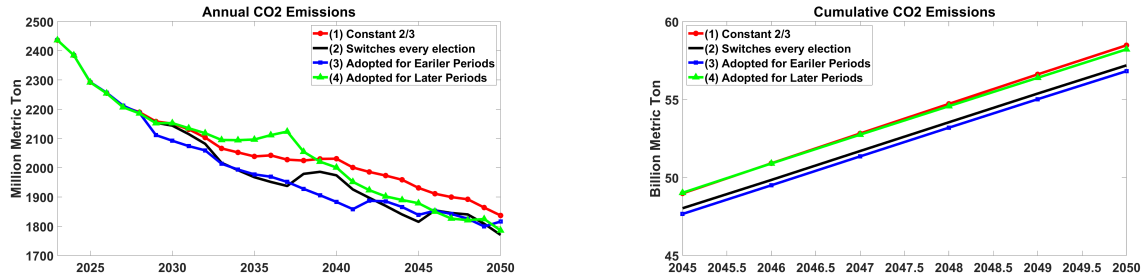
Figure 12: Annual CO_2 Emissions (2022-2050) and Cumulative CO_2 Emissions (2045-2050)

goal, pledged by many governments, including the US's, may require strict policies focused on the periods close to the target year as in the scenarios (2) and (4). However, considering the long-lasting global warming effects of CO_2, these results may signal that even with a possibility of it being abandoned or weakened in the future, a climate policy should start early with the highest stringency possible to curb climate change as in (2) and (3).

In addition to the relationship between timing and emissions, abatement costs would provide a perspective on the significance of policy timing. Table 4 shows that (3) *Earlier Adoption* scenario results in the lowest abatement cost, only 66% of (4) *Later Adoption*. Another noteworthy result is that although (2) *Frequent Switch* scenario might be considered to be effective, with relatively lower annual and cumulative emissions, the scenario's abatement cost is 30% higher than (3) *Earlier Adoption*'s cost. Despite their comparatively smaller variations in annual and cumulative

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Table 3: CO_2 Emissions by Scenario

	Emissions in 2050 (Million Metric Tons)	Cumulative Emissions (between 2022-2050) (Million Metric Tons)
(1) *Constant 2/3*	1,836.65	60,352
(2) *Frequent Switch*	1,770.24	59,000
(3) *Earlier Adoption*	1,815.92	58,675
(4) *Later Adoption*	1,785.51	60,044

Table 4: Abatement Costs by Scenario

	Abatement Costs (USD / Metric Ton)
(1) *Constant 2/3*	170.08
(2) *Frequent Switch*	186.63
(3) *Earlier Adoption*	144.37
(4) *Later Adoption*	217.27

emissions, scenarios show meaningful differences in average abatement costs.

The distribution of electricity sector abatement costs from 1,000 simulations (5th-95th percentile) is displayed in Figure 13 and also the distribution with respect to annual emissions and cumulative emissions is plotted in Figure 14. The median value is $173.15 per metric ton of CO_2. The scenarios with abatement costs lower than the median value are located in the upper left part in Figure 14 and are characterized with lower cumulative emissions and earlier adoption of policy. The results of annual and cumulative emissions and abatement costs highlight that even when the environmental impacts of policy scenarios with different implementation schedules are similar, the schedules are rather critical in determining the efficiency of pathways. It is suggested that earlier adoption could be more efficient in reducing emissions with lower abatement costs.
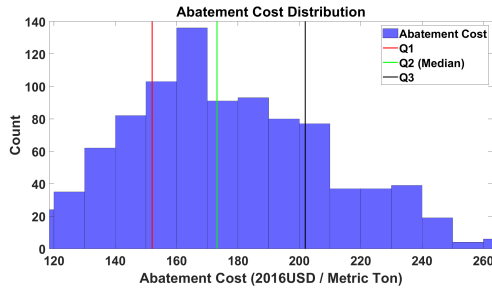
Figure 13: Abatement Costs Distribution from 1,000 simulations (5th-95th percentile)
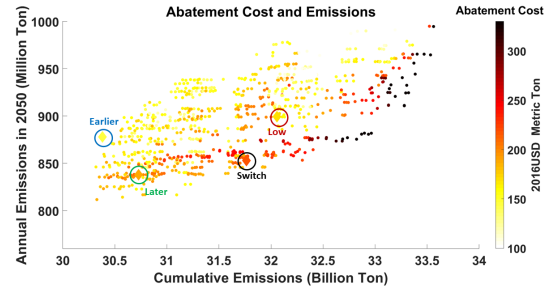
Figure 14: Relationship between Abatement Costs and Emissions

4.4 Effects of Learning-by-Doing

4.4.1 Interaction with Policy Uncertainty

The basic model used for the analyses above assumes overnight capital costs for power plants and transportation stock prices follow exogenous trends, implying that cost reductions take place autonomously over the simulation period, regardless of the amount and timing of investment. This assumption might be to some extent unrealistic and need to be relaxed, especially, for this type of a study that addresses the impacts of timings of investment and subsidy. Government subsidies for new low-emitting technologies are often supported on the grounds of learning-by-ding externalities together with environmental externalities (Van Benthem et al., 2008). Thus, incorporating endogenous technological growth allows a more realistic analysis of government subsidies for renewables and electric vehicle. To this end, this section examines the simulation results from an extended model that incorporates learning-by-doing (LBD) effects in capital investment costs, formulated as in Section 3.1.3 and compares them with those from the basic model simulations.

First, the investment in renewable electricity projected from the LBD model (Figure 16) shows 16-24% higher results than from the basic model without LBD (Figure 15) across four sample scenarios presented in Section 4.1. This can be partially explained by the characteristics of LBD effects. In terms of the basic model, the investment timing and volume is mainly driven by the policy uncertainty and returns on the invested capital. In addition to those factors, in the LBD

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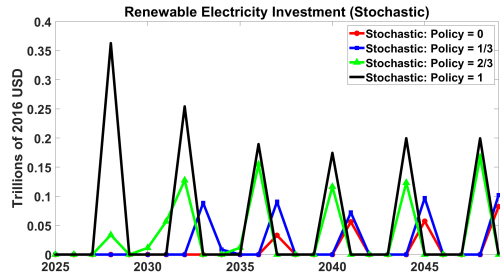
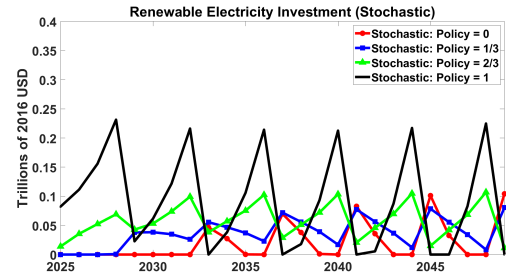Figure 15: Renewable Investment without LBD

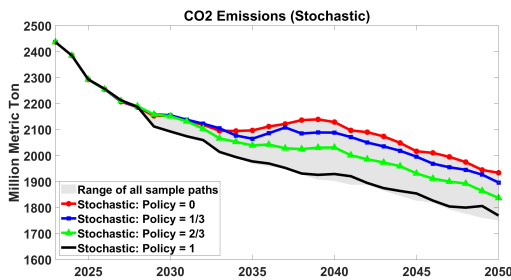Figure 16: Renewable Investment with LBD
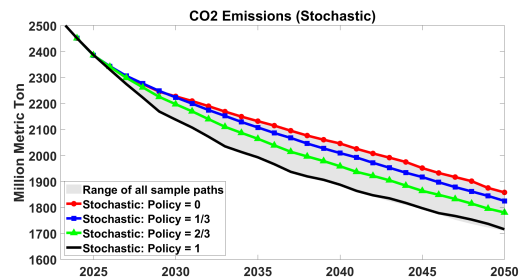

Figure 17: Annual CO2 Emissions without LBD

Figure 18: Annual CO2 Emissions with LBD

model, the cost-reduction effects of investment lead to relatively sustained and regular investment throughout the simulation period, rather than few bunching of investment around the policy transition years as exhibited in the basic model. As a consequence, annual CO_2 emissions is 3-4% lower in 2050 (Figures 17-18). One noteworthy finding is that transition to lower-emitting technology accelerates later relative to no-LBD model, after capital cost is reduced to a certain degree. This result is consistent with the implication in Rasmussen (2001) that technological progress induced by LBD does not necessarily guarantee expedited investment in the near-term and could delay the abatement efforts.

4.4.2 Interaction with Policy Timing

This section examines the effects of policy timing using the LBD-incorporated model and compare the results with those from the basic model. Although two model results show similar patterns, the model with LBD, in general, shows lower annual emissions, yet higher cumulative emissions compared to the basic model (Table 5). This trend is consistent with the previous section results that adopting LBD effects in the model leads to even later abatement efforts. However, when costs are reduced to a degree that returns on capital become higher, investment on abatement technologies accelerates, thus achieving lower emissions in 2050. When comparing with CO_2 emissions between the LBD stochastic model and the basic deterministic model (the model without incorporating uncertainty and LBD), the latter might over-project CO_2 emissions and underestimate the impacts of subsidies even more.

Table 5: CO_2 Emissions Comparison

	Without LBD	With LBD
Annual Emissions in 2050 (Million Metric Ton)		
(1) *Constant 2/3*	1,836.6	1,780.5
(2) *Frequent Switch*	1,770.2	1,717.0
(3) *Earlier Adoption*	1,815.9	1,784.8
(4) *Later Adoption*	1,785.5	1,719.3
Cumulative Emissions (Million Metric Ton)		
(1) *Constant 2/3*	60,352	60,407
(2) *Frequent Switch*	59,000	59,379
(3) *Earlier Adoption*	58,675	59,151
(4) *Later Adoption*	60,044	60,443

As the LBD-model is associated with lower annual emissions in later period and higher accumulated emissions throughout the simulation period, its abatement cost estimates are expectedly higher than the model with LBD, around 1.3-1.7 times. Figure 19 shows the electricity sector abatement cost distribution from 1,000 simulations (5th-95th percentile). The median abatement
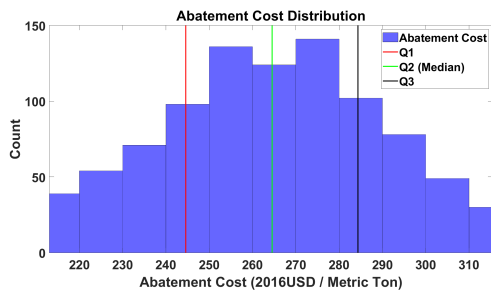
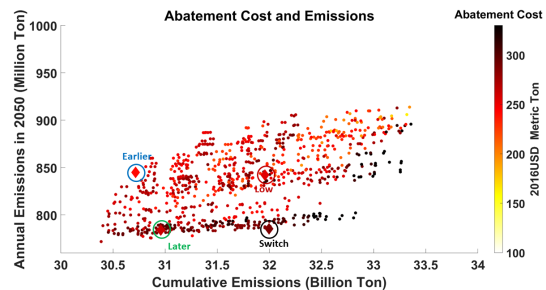Figure 19: Abatement Costs Distribution from 1,000 simulations (5th-95th percentile)

Figure 20: Relationship between Abatement Costs and Emissions

cost is estimated to be \$264.52 per metric ton of CO_2, which is much higher than \$173.15 without LBD. The difference can be noticeable in the Figure 20 where the abatement costs distribution is shifted downward and to the right, relative to that from no-LBD model. This is partially driven by the LBD effects contributing to the delay of abatement investment. The results in this section reinforce the significance of modeling approach choices in a climate policy analysis.

5   Conclusion

This paper investigates the effects of uncertainty in stringency and schedule of climate policy implementation using the recently-signed IRA bill as a policy reference. An optimal growth model incorporating a detailed representation of major CO_2-emitting sectors is developed for the US economy. Policy uncertainty module characterized with four possible policy states and a transition matrix is added to the model to account for the stochastic nature of the US climate policy. This non-stationary dynamic stochastic model is solved using the new computational method, SCEQ, through the mid-century.

First, the analysis about uncertainty effects focuses on investment and outputs from electricity generation and transportation sector, and abatement costs and CO_2 emissions. Stochastic model results, in general, show a wider range of possible outcomes, underscoring that if an environmental

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policy is uncertain in nature, just as in the US, it may requires a stochastic model to make an analysis complete. How optimal investment decisions respond to policy uncertainty relies on the today's and future expected policy stringency. Compared to their respective deterministic results, a stringent policy scenario tends to observe an earlier action of investment, expecting lower subsidies in the future, whereas a scenario with a lenient policy regime experiences delays or reductions in investment today, waiting for a more generous monetary incentive in the future. Interestingly, the stochastic model projects lower CO_2 emissions for all scenarios, relative to deterministic model. Lastly, the results suggest that policy uncertainty may increase abatement costs due to inefficient intertemporal allocation of investment and subsidies.

The second analysis pays attention to a political economic aspect of policy uncertainty. The result implies that a more durable and certain policy regime may prevent boom-bust cycles and lead to more efficient use of resources and lower abatement costs. The analysis sheds light on the role of policy certainty in CO_2 emissions mitigation.

Third, the effects of policy implementation timing are also shown to be substantial. A set of policy scenarios are compared to explain how the differential schedules of equally stringent policy lead to heterogeneous outcomes. The scenarios with later adoption serve better the purpose of reducing CO_2 emissions in 2050 than the scenario with earlier adoption and later abandonment. Nevertheless, incentivizing lower-emitting technologies with a policy in earlier periods, though discontinued later, seems to be more effective in mitigating global warming as the scenario lowers the cumulative GHG emissions through 2050. At the same time, earlier adoption is efficient as the abatement costs associated with earlier subsidies are estimated to be lower than that with later subsidies. The timing of policy implementation under uncertainty is worth to discuss in the context that the US is the world's second largest emitter of CO_2 and has an influence on other countries in the globe.

Lastly, the study presents three different models–deterministic model, stochastic model without LBD, and stochastic model with LBD–to demonstrates different specifications of models result in differential results in investment timing and volumes, CO_2 emissions, and abatement costs. The

comparisons have implications for the choice of model specifications depending on the characteristics of policy to be examined and the societal context and the technologies of interest.

All results from the basic model are tested with different specification of Markov transition matrix for a sensitivity analysis. Policy instruments incorporated in the current paper are shown to be insensitive to specification of transition matrix, but still it would raise a question about how to better construct a transition matrix in the Markov process to represent policy uncertainty and address the political environment of the country, which is partially hinted in Section 4.2. The question has been recently paid attention to by scholars who figured that political feasibility is only dynamic and evolving over time (Jewell and Cherp, 2020) and climate policy is determined by socio-politico-technical feedback processes (Moore et al., 2022). Developing a realistic and dynamic uncertainty module may require a global-scale integrated assessment model and is left for future research.

The research's contributions to the literature are threefold. First, it attempts to incorporate climate policy uncertainty in a dynamic model with multiple sectors. This approach is underdeveloped even when it is necessary for the countries politically polarized over environmental policies, like the US. Second, explicitly modeling the schedule of policy implementation is another novelty of the study. This approach enables the analysis of comparing a wide range of scenarios in terms of their economic and environmental outcomes and the efficiency and effectiveness of climate policies depending on policy adoption timing. Lastly, the research makes a rare attempt to examine the interaction of climate policy uncertainty and learning-by-doing effects. It underscores the significance of model specification in a climate policy analysis.

Still, the research requires further improvement. First, to analyze the process of economy-wide decarbonization, the economic model needs to incorporate the CO_2 emissions from all sectors and their emissions reduction channels. Manufacturing sectors, including steel, aluminum, and cement, account for over 20% CO_2 emissions in the US and thus are a critical part of a climate policy analysis. Similarly, the analysis of the IRA and potential future legislation is not complete as the model focuses only on investment tax credit, leaving out other instruments, such as production

tax credit, for instance, for renewable and clean electricity. By including other climate provisions of the IRA, the analysis can consider their interactions under uncertainty as well. Another factor that is critical, but missing in the study is trade. The results might differ if the model includes trade flows of primary energy, raw materials, vehicles and technologies. In addition, to more explicitly account for the impacts of tax credits and recycling, it is required to transform the model into a dynamic general equilibrium model. Lastly, the political uncertainty is characterized using an ad-hoc probabilities, though tested with a set of different specifications. Despite a perfect representation of political feasibility being a remotely possible idea, it can improve by considering relevant factors, such as temperature, trends of natural disasters, and global trade and energy price.

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Appendix

A   Model Parameters

Table 6: Baseline Parameters

Parameter	Description	Units	Value
Utility and Population			
β	Social Discount Factor		0.97172
η	Risk Aversion Parameter (and Inverse of Intertemporal Elasticity of Substitution)		2.25292527
pop_0	US Population in 2016	Million People	323.128
Resource Extraction			
$Stock_0^{coal}$	Coal Estimated Recoverable Reserves	Billion Short Tons	254.896
$Stock_0^{gas}$	Natural Gas Total Technically Recoverable Resources	Trillion Cubic Feet	2,462
$Stock_0^{oil}$	Crude Oil Total Technically Recoverable Resources	Billion Barrels	285
F_0^{coal}	Coal Extraction in 2016	Billion Short Tons	0.6786
F_0^{gas}	Natural Gas Extraction in 2016	Trillion Cubic Feet	27.44422
F_0^{oil}	Crude Oil Extraction in 2016	Billion Barrels	6.275878
γ^{coal}	Coal Extraction Cost Function Parameter		2.3554
γ^{gas}	Natural Gas Extraction Cost Function Parameter		4.7426
γ^{oil}	Crude Oil Extraction Cost Function Parameter		1.8385
$g^{\gamma,gas}$	Decline Rate of Natural Gas Extraction Cost		0.082107
$g^{\gamma,oil}$	Decline Rate of Crude Oil Extraction Cost		0.041873
$d^{\gamma,gas}$	Growth Rate of Natural Gas Extraction Cost		0.0043258
$d^{\gamma,oil}$	Decline Rate of Crude Oil Extraction Cost		0.012288
a^{reg}	Coal Supply Regulation Cost Growth Rate		0.071292
b^{reg}	Initial Coal Supply Regulation Unit Cost	Thousand 2016 USD / Short Ton	0.0014671

Table 5: Baseline Parameters (continued)

Parameter	Description	Units	Value
Fossil Fuel Electricity Generation			
K_0^{coal}	Coal Power Plant Net Summer Capacity	Terawatts	0.2666199
K_0^{gas}	Natural Gas Power Plant Net Summer Capacity	Terawatts	0.4468232
$Fuel_0^{coal}$	Coal Use for Electricity Generation in 2016	Billion Short Tons	0.6786
$Fuel_0^{gas}$	Natural Gas Use for Electricity Generation in 2016	Trillion Cubic Feet	9.98527
$Elec_0^{coal}$	Coal Electricity Generation in 2016	1,000 Terawatt Hours	1.239149
$Elec_0^{gas}$	Natural Gas Electricity Generation in 2016	1,000 Terawatt Hours	1.379271
$\omega^{coal,fuel}$	Share of Coal in Coal Electricity CES Production Function		0.173646122
$\omega^{gas,fuel}$	Share of Natural Gas in Natural Gas Electricity CES Production Function		0.67946819
ρ^{coal}	Elasticity Parameter between Coal and Generation Capacity Inputs in Coal Electricity CES Production Function		-2.466589155
ρ^{gas}	Elasticity Parameter between Natural Gas and Generation Capacity Inputs in Natural Gas Electricity CES Production Function		-0.326650455
g^{coal}	Growth Rate of TFP for Coal Electricity Generation		0.003233739
g^{gas}	Growth Rate of TFP for Natural Gas Electricity Generation		0.001002627
d^{coal}	Decline Rate of TFP for Coal Electricity Generation		0.240699483
d^{gas}	Decline Rate of TFP for Natural Gas Electricity Generation		0.199947368
δ^{ff}	Depreciation Rate for Fossil Fuel-fired Electricity Generation Capacity		0.049780949

Table 5: Baseline Parameters (continued)

Parameter	Description	Units	Value
Renewable Electricity Generation			
K_0^{solar}	Coal Power Plant Net Summer Capacity	Terawatts	0.032958
K_0^{wind}	Natural Gas Power Plant Net Summer Capacity	Terawatts	0.0812866
$Elec_0^{solar}$	Coal Electricity Generation in 2016	1,000 Terawatt Hours	0.054866
$Elec_0^{wind}$	Natural Gas Electricity Generation in 2016	1,000 Terawatt Hours	0.226993
α^{solar}	Output Elasticity of Solar Power Capacity		0.427572491
α^{wind}	Output Elasticity of Wind Power Capacity		0.326798148
g^{solar}	Growth Rate of TFP for Solar Electricity Generation		0.312143141
g^{wind}	Growth Rate of TFP for Wind Electricity Generation		0.208899549
d^{solar}	Decline Rate of TFP for Solar Electricity Generation		0.173927025
d^{wind}	Decline Rate of TFP for Wind Electricity Generation		0.318891635
δ^{renew}	Depreciation Rate for Renewable Electricity Generation Capacity		0.045841669
Learning-by-Doing Effects			
b^{gas}	Learning Rate Parameter for Natural Gas Power Plant Installation		0.252848611
b^{solar}	Learning Rate Parameter for Solar Power Plant Installation		0.263357537
b^{wind}	Learning Rate Parameter for Wind Power Plant Installation		0.18951335
$b^{electric}$	Learning Rate Parameter for Electric Vehicle Production		0.10627491
c^{solar}	Solar Power Plant Capital Cost Parameter		0.971143565
c^{wind}	Wind Power Plant Capital Cost Parameter		0.999480474
$c^{electric}$	Electric Vehicle Production Cost Parameter		0.994104587
c^{gas}	Natural Gas Power Plant Capital Cost Parameter		0.998394969

Table 5: Baseline Parameters (continued)

Parameter	Description	Units	Value
Transportation			
$K_0^{M,gasoline}$	Light-Duty Gasoline Vehicle Stock in 2016	Millions	114.517975
$K_0^{M,electric}$	Light-Duty Electric Vehicle Stock in 2016	Millions	0.272337
$M_0^{gasoline}$	Vehicle Miles Traveled by Light-Duty Gasoline Vehicles in 2016	Billion Miles	2407.781738
$M_0^{electric}$	Vehicle Miles Traveled by Light-Duty Electric Vehicles in 2016	Billion Miles	4.190919
$Fuel_0^{M,gasoline}$	Gasoline Use for Light-Duty Gasoline Vehicle in 2016	Billion Barrels	3.658204
$Fuel_0^{M,electric}$	Electricity Use for Light-Duty Electric Vehicle in 2016	1,000 Terawatt Hours	0.007497
$\omega^{M,gasoline}$	Gasoline Input Share in Vehicle Miles Traveled CES Function		0.44117
$\omega^{M,electricity}$	Electricity Input Share in Vehicle Miles Traveled CES Function		0.47583
$\rho^{M,gasoline}$	Elasticity Parameter between Gasoline and Vehicle Stock Inputs in Gasoline Vehicle Miles Traveled CES Function		-3.455
ρ^{EV}	Elasticity Parameter between Electricity and Vehicle Stock Inputs in Electric Vehicle Miles Traveled CES Function		-2.5393
$g^{M,gasoline}$	Growth Rate of Efficiency for Gasoline Vehicles		0.0033565
$g^{M,EV}$	Growth Rate of Efficiency for Electric Vehicles		0.3078
$d^{M,gasoline}$	Decline Rate of Efficiency for Gasoline Vehicles		0.020734
$d^{M,EV}$	Decline Rate of Efficiency for Electric Vehicles		0.13296
$\delta^{M,gasoline}$	Depreciation Rate for Gasoline Vehicles		0.10557
$\delta^{M,EV}$	Depreciation Rate for Electric Vehicles		0.07015
$\alpha^{M,gasoline}$	Returns to Scale Parameter in Gasoline Vehicle Miles Traveled CES Function		0.33647
$\alpha^{M,electric}$	Returns to Scale Parameter in Electric Vehicle Miles Traveled CES Function		0.40261

Table 5: Baseline Parameters (continued)

Parameter	Description	Units	Value
Final Goods and Services Sector			
K_0^G	Capital Stock in 2016	Trillion 2016 USD	64.65
Y_0^G	Gross Domestic Product in 2016	Trillion 2016 USD	18.6951
M_0^G	Vehicle Miles Traveled in 2016	Billion Miles	2425.77
$Elec_0^G$	Electricity Consumption in 2016	1,000 Terawatt Hours	4.155
$F_0^{oil,G}$	Petroleum Product Used for Production (Excluding Transportation)	Billion Barrels	2.618
$F_0^{gas,G}$	Natural Gas Used for Production (Excluding Electricity Generation)	Trillion Cubic Feet	17.459
ω^k	Capital Input Share in CES Production Function		0.90772
ω^{elec}	Electricity Input Share in CES Production Function		0.49549
ω^m	Transportation Input Share in CES Production Function		0.21424
ω^{oil}	Oil Input Share in CES Production Function		0.40622
ω^L	Labor Input Share in CES Production Function		0.22286
ρ^{kem}	Elasticity Parameter between Transportation and Capital-Energy Composite Inputs in CES Production Function		-0.26656
ρ^{ke}	Elasticity Parameter between Capital and Energy Inputs in CES Production Function		0.28649
ρ^{en}	Elasticity Parameter between Electricity and Primary Energy Composite Inputs in CES Production Function		-2.138
g^G	Growth Rate of TFP for Production		0.0096
d^G	Decline Rate of TFP for Production		0.0059
δ^G	Depreciation Rate for Capital Stock		0.10266
ρ^{pe}	Elasticity Parameter between Petroleum and Natural Gas Inputs in CES Production Function		-3.7655
ρ^G	Elasticity Parameter between Labor and Capital-Energy-Transportation Composite Inputs in CES Production Function		-0.0054

B Calibration: Model without Learning-by-Doing

All model parameters are calibrated such that the sum of L2 norms between the model outcomes and corresponding BEA and EIA 2016-2021 reference data and EIA projection after 2021 is minimized. The outcomes to be examined include electricity generation and capacity, vehicle stocks and miles traveled, and GDP growth.
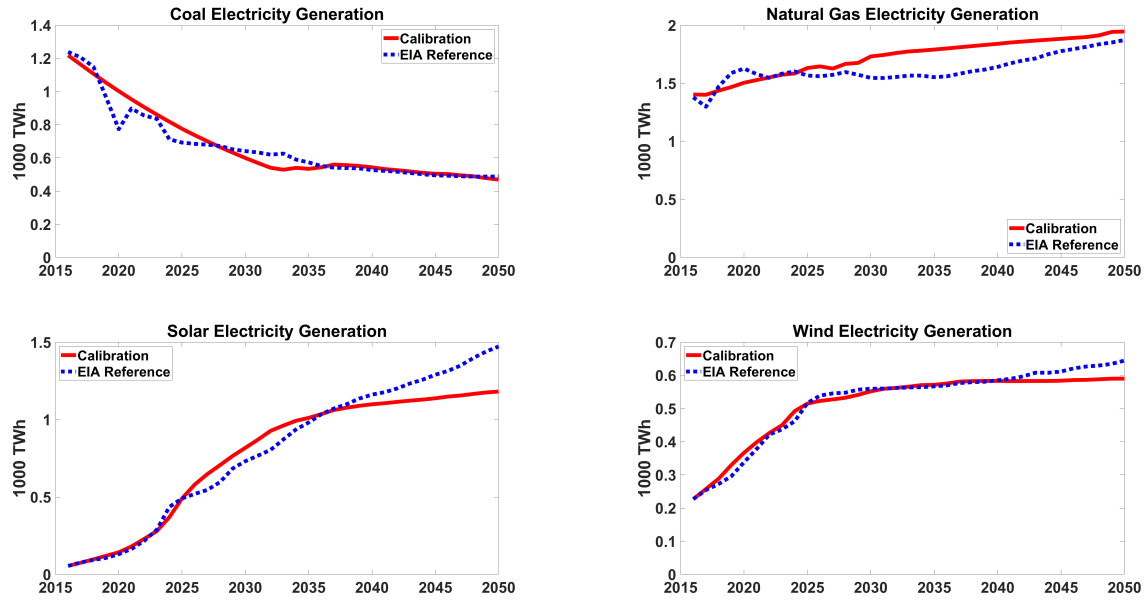
Figure 21: Electricity Generation Calibration
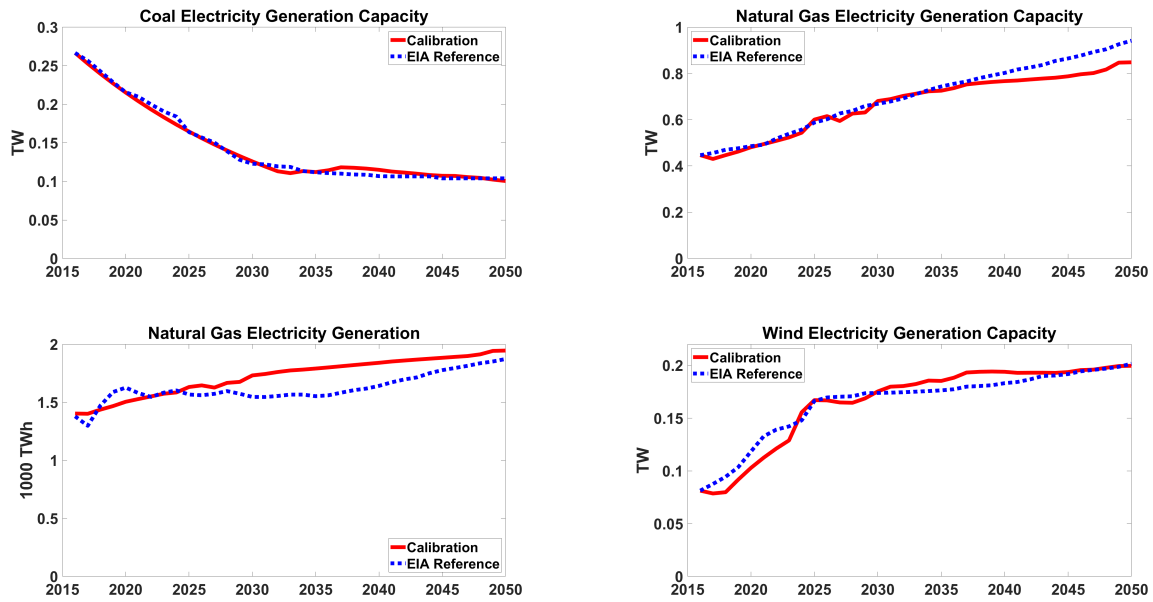
Figure 22: Electricity Generation Capacity Calibration
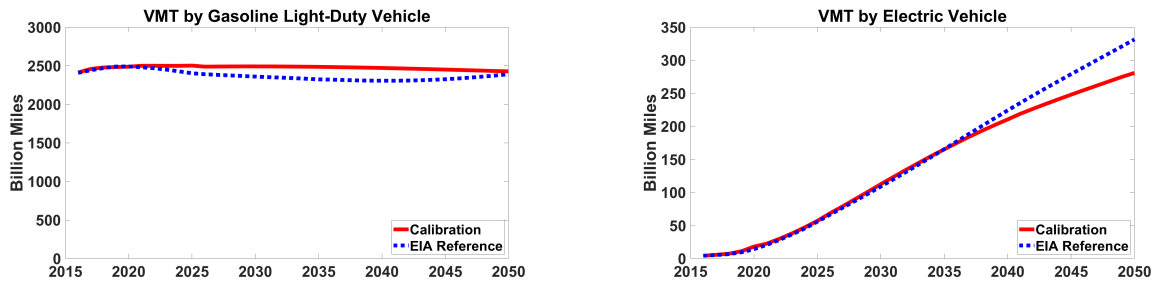
Figure 23: Vehicle Miles Traveled Calibration
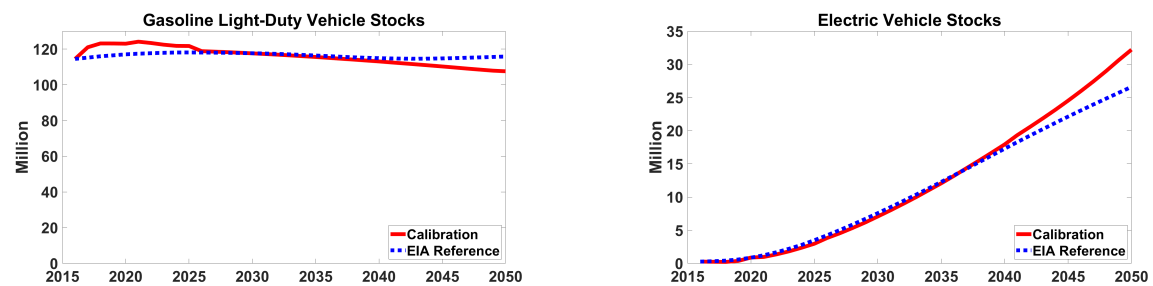
Figure 24: Vehicle Stock Calibration

EIA AEO 2022 Reference scenario assume the GDP growth rate equals 2.2%.
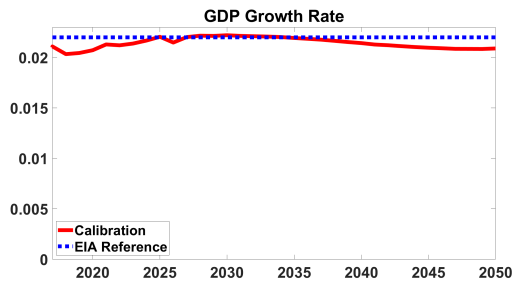
Figure 25: GDP Growth Rate

Figure 26 compares sectoral and aggregate CO2 emissions drawn from the calibrated model and EIA reference projection.
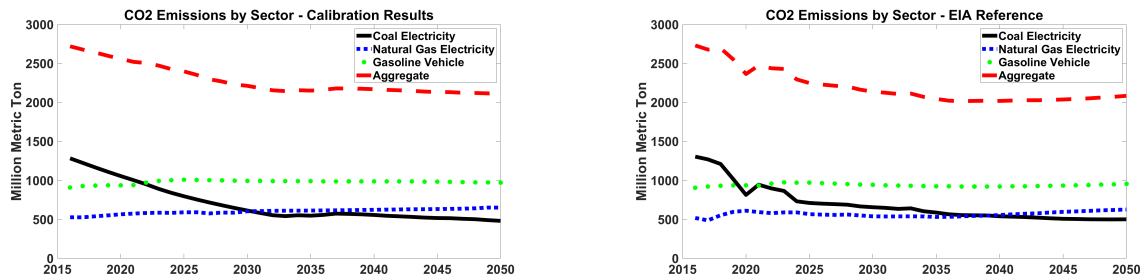
Figure 26: CO2 Emissions for Baseline

C   Calibration: Model with Learning-by-Doing

The extended model with learning-by-doing effects is based on the main model without learning-by-doing. Calibration performs with respect to overnight capital costs of natural gas, wind, and solar power plants and electric vehicle prices. Coal power plant capital cost and gasoline vehicle price assume to follow the EIA baseline projection.
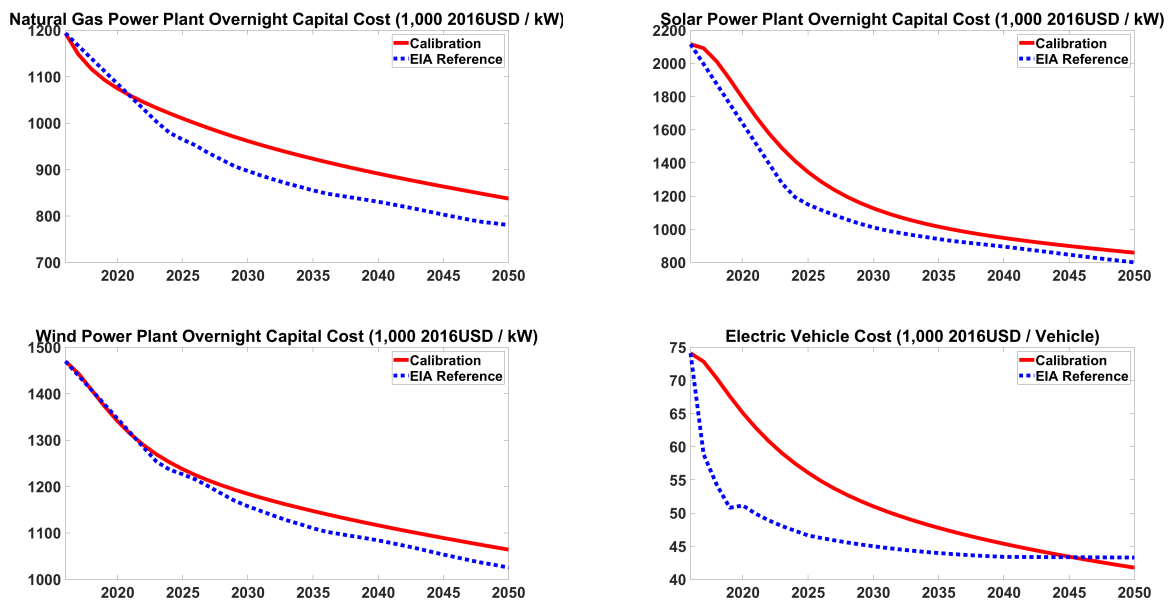
Figure 27: Capital Investment Cost Calibration
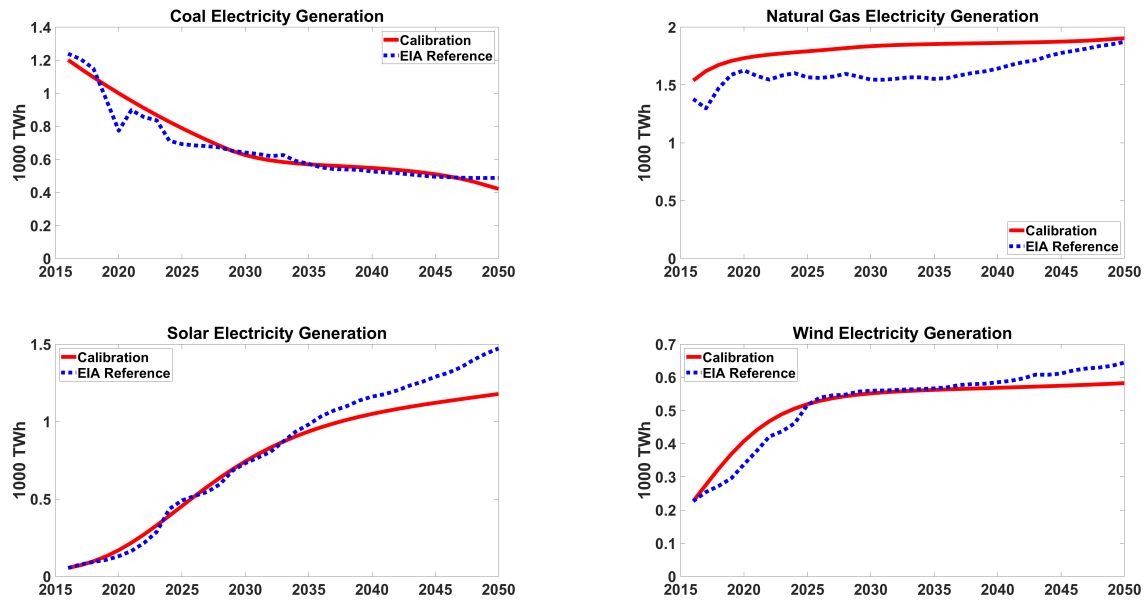
Figure 28: Electricity Generation Calibration
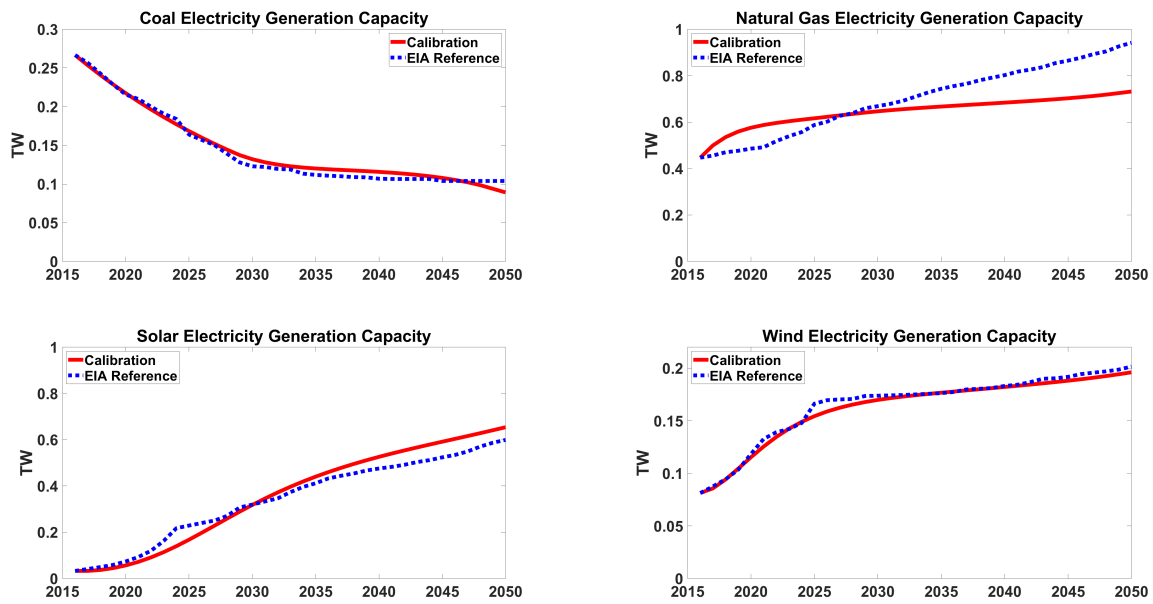
Figure 29: Electricity Generation Capacity Calibration
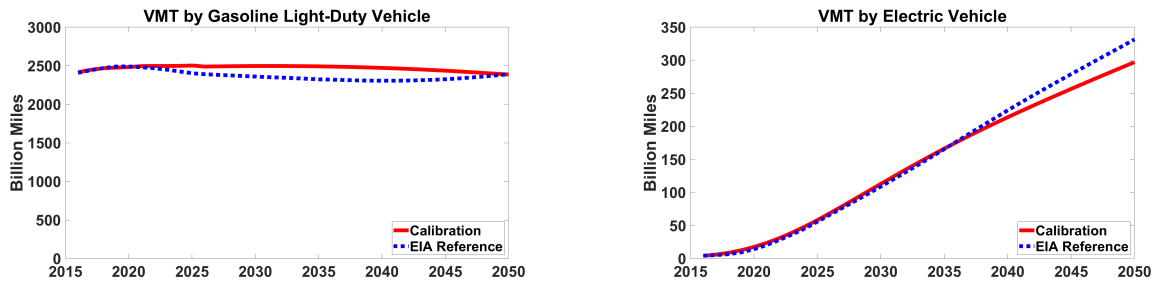
Figure 30: Vehicle Miles Traveled Calibration
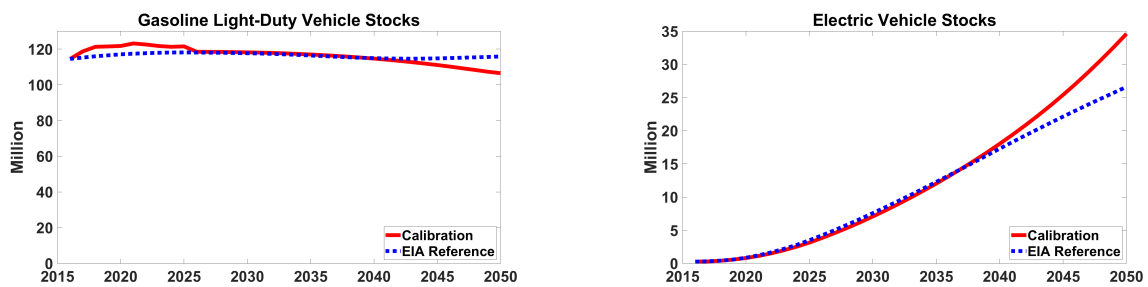
Figure 31: Vehicle Stock Calibration

EIA AEO 2022 Reference scenario assume the GDP growth rate equals 2.2%.
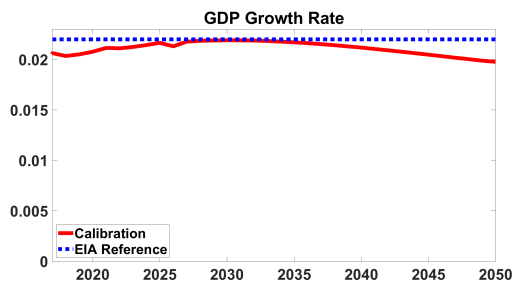
Figure 32: GDP Growth Rate

Figure 33 compares sectoral and aggregate CO2 emissions drawn from the calibrated model and EIA reference projection.
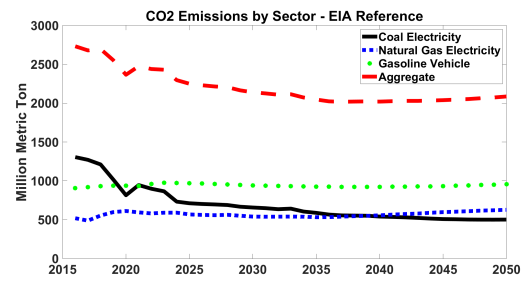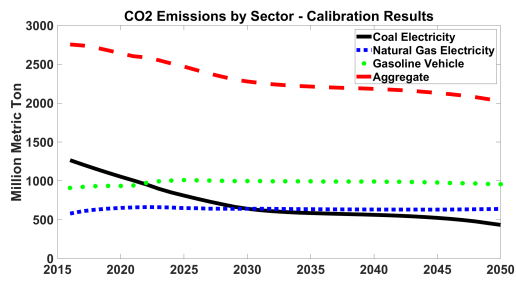
Figure 33: CO2 Emissions for Baseline

D   Model Description

D.1   Planner's Problem

The social planner maximizes the expected social welfare,

$$max \, \mathbb{E} \left\{ \sum_{t=0}^{T-1} \beta^t \frac{(C_t/Pop_t)^{1-\eta}}{1-\eta} Pop_t \right\} \tag{3}$$

, subject to the budget constraint,

$$Y_t^G = C_t + I_t^G + \sum_{s \in ELEC} I_t^s + \sum_{s \in TRANS} I_t^s + \sum_{s \in FF} Z_t^s \tag{4}$$

, where G represents the final goods and services sector, I^s is sectoral investment, Z is the extraction cost of fossil fuels, $FF = \{coal, crude\,oil, and\,natural\,gas\}$, $ELEC = \{coal, natural\,gas, solar, and\,wind\}$, $ELEC.FF = \{coal, natural\,gas\}$, and $TRANS = \{gasoline, electricity\}$.

D.2   Resource (Fuel) Extraction

The cost of extraction for $s \in FUEL$ increases as the stock decreases, expressed as

$$Z_t^s = A_t^s \left(\frac{F_t^s}{Stock_t^s} \right)^{\gamma^s} \tag{5}$$

where A_t^s represent technological advancement in extraction.

The resource stock transition follows

$$Stock_{t+1}^s = Stock_t^s - F_t^s \tag{6}$$

D.3   Fossil Fuel Electricity Generation

A fossil fuel electricity production function for $s \in ELEC.FF$ is a CES function of fuel and capacity,

$$\frac{Elec_t^s}{Elec_0^s} = A_t^s \left[\omega^{s,fuel} \left(\frac{Fuel_t^s}{Fuel_0^s} \right)^{\rho^s} + \left(1 - \omega^{s,fuel} \right) \left(\frac{K_t^s}{K_0^s} \right)^{\rho^s} \right]^{\frac{1}{\rho^s}} \tag{7}$$

.The capacity transition follows

$$K_{t+1}^s = \left(1 - \delta^{ff} \right) K_t^s + \frac{I_t^s}{p_t^s} \tag{8}$$

, where K_t^s indicates the power generation capacity in TW unit and p_t^s represents the overnight capital cost of plant installation (per TW) for sector s. The EIA provides the projection (reference scenario) until 2050, and after 2050 the cost is extrapolated.

D.4   Renewable Electricity Generation

The renewable electricity generation ($s = solar, wind$) takes a single input, generation capacity, and the rest is assumed to be implicitly reflected in the productivity parameter, A_t^s,

$$\frac{Y_t^s}{Y_0^s} = A_t^s \left(\frac{K_t^s}{K_0^s} \right)^{\alpha^{s,k}} \tag{9}$$

and the capacity transition follows

$$K_{t+1}^s = \left(1 - \delta^{nf} \right) K_t^s + \frac{I_t^s}{\left(1 - \tau_t^{renew}(X_t) \right) p_t^s} \tag{10}$$

. τ_t^{renew} is the investment tax credits for solar and wind power plants and is a function of the policy state, X_t. Since the focus of the research lies in coal, natural gas, solar and wind electricity, and a large portion of the rest electricity generating capacity, including hydroelectric power generation and conventional nuclear power generation, is hard to change, I assume that the aggregate of the rest electricity generation does not change over time.

D.5 Transportation

The transportation sector considers only light-duty gasoline cars and trucks and light-duty electric cars ($s = gasoline, electric$). The vehicle miles traveled, M_t^s, is a CES function of fuels, gasoline or electricity, and vehicle stocks:

$$M_t^s = A_t^s \left[\omega^{M,s} \left(\frac{Fuel_t^M}{Fuel_0^M} \right)^{\rho^s} + \left(1 - \omega^{M,s}\right) \left(\frac{K_t^{M,s}}{K_0^{M,s}} \right)^{\rho^s} \right]^{\frac{\alpha^s}{\rho^s}} \tag{11}$$

and the car stock evolves following

$$K_{t+1}^{M,gasoline} = \left(1 - \delta^M\right) K_t^{M,gasoline} + \frac{I_t^{M,gasoline}}{p_t^{M,gasoline}} \tag{12}$$

and

$$K_{t+1}^{M,electric} = \left(1 - \delta^M\right) K_t^{M,electric} + \frac{I_t^{M,electric}}{\left(p_t^{M,electricity} - \tau_t^{electric}(X_t) \right)} \tag{13}$$

where $p_t^{M,s}$ is projected car sales price. Medium- and heavy-duty trucks are not included in the transportation and considered to be aggregated into general capital stock as they are used mainly for industrial sectors. Other light-duty vehicles, including hybrid and diesel, are ignored as the major substitution between electric and gasoline cars is the main focus of the study. $\tau_t^{electric}(X_t)$ represents the tax credit for a electric vehicle purchase given the realized policy state X_t.

D.6 Final Goods and Services

The final good production function is constructed with a Cobb-Douglas function and nested CES functions:

$$\frac{Y_t}{Y_{0t}} = A_t^G \left[\omega^L \left(\frac{L_t}{L_0} \right)^{\rho^G} + \left(1 - \omega^L\right) \left(Q_t^{KEM}\right)^{\rho^G} \right]^{\frac{1}{\rho^G}} \tag{14}$$

where

$$Q_t^{KEM} = \left[\omega^m \left(\frac{M_t^G}{M_0^G} \right)^{\rho^{kem}} + (1 - \omega^m) \left(Q_t^{KE} \right)^{\rho^{kem}} \right]^{\frac{1}{\rho^{kem}}} \tag{15}$$

,

$$Q_t^{KE} = \left[\omega^k \left(\frac{K_t^G}{K_0^G} \right)^{\rho^{ke}} + \left(1 - \omega^k \right) \left(Q_t^{EN} \right)^{\rho^{ke}} \right]^{\frac{1}{\rho^{ke}}} \tag{16}$$

,

$$Q_t^{EN} = \left[\omega^{elec} \left(\frac{Elec_t^G}{Elec_0^G} \right)^{\rho^{en}} + \left(1 - \omega^{elec} \right) \left(Q_t^{PE} \right)^{\rho^{en}} \right]^{\frac{1}{\rho^{en}}} \tag{17}$$

, and

$$Q_t^{PE} = \left[\omega^{oil} \left(\frac{F_t^{oil,G}}{F_0^{oil,G}} \right)^{\rho^{pe}} + \left(1 - \omega^{oil} \right) \left(\frac{F_t^{gas,G}}{F_0^{gas,G}} \right)^{\rho^{pe}} \right]^{\frac{1}{\rho^{pe}}} \tag{18}$$

The capital stock's law of motion follows

$$K_{t+1}^G = \left(1 - \delta^G \right) K_t^G + I_t^G \tag{19}$$

D.7   Market Clearing

$$F_t^{coal} = Fuel_0^{coal} \tag{20}$$

$$F_t^{gas} = Fuel_0^{gas} + F_0^{gas,G} \tag{21}$$

$$F_t^{oil} = Fuel_0^{M,gasoline} + F_0^{oil,G} \tag{22}$$

$$E_t^{coal} + E_t^{gas} + E_t^{solar} + E_t^{wind} + E^{other} = E_t^G + Fuel_t^{M,electric} \tag{23}$$

D.8 Others

Coal supply regulation cost is assumed to grow as

$$regulation\text{-}cost_t = b^{reg}e^{a^{reg}(t-1)} \tag{24}$$

TFP for each sector, s, is formulated as

$$A_t^s = e^{\frac{g^s}{d^s}\left(1-e^{-d(t-1)}\right)} \tag{25}$$

E Sensitivity Analysis

This section tests simulations with different Markov probability distribution. It provides a sensitivity analysis and shows how robust the results are to different specification of Markov transition, shown in Table 7.

Each column of transition probability corresponds to each column of plots in subsections E.1 and E.2.

(1)	(2)	(3)
$\mathbf{P}_t = \begin{pmatrix} 0.2 & 0.5 & 0.3 & \\ 0.35 & 0.2 & 0.35 & 0.1 \\ 0.1 & 0.35 & 0.2 & 0.35 \\ & 0.3 & 0.5 & 0.2 \end{pmatrix}$	$\mathbf{P}_t = \begin{pmatrix} 0.6 & 0.3 & 0.1 & \\ 0.15 & 0.6 & 0.15 & 0.1 \\ 0.1 & 0.15 & 0.6 & 0.15 \\ & 0.1 & 0.3 & 0.6 \end{pmatrix}$	$\mathbf{P}_t = \begin{pmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \end{pmatrix}$

Table 7: Three Types of Transition Probability

E.1 Effects of Uncertainty

(1)   (2)   (3)
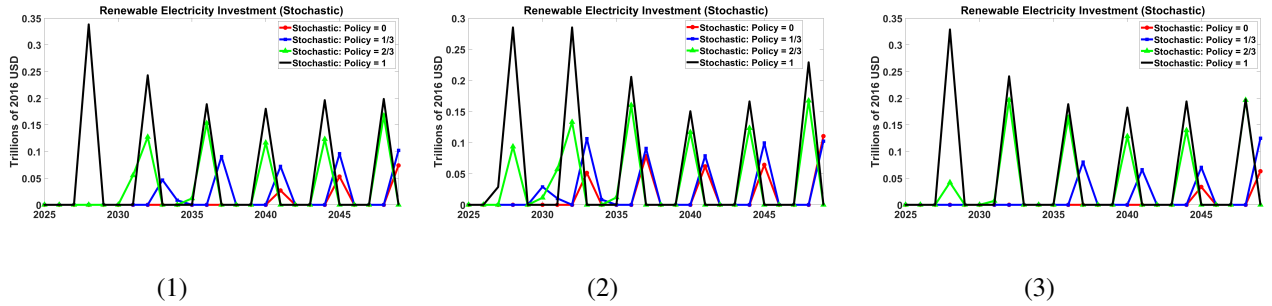
Figure 34: Renewable Electricity Investment

(1)   (2)   (3)
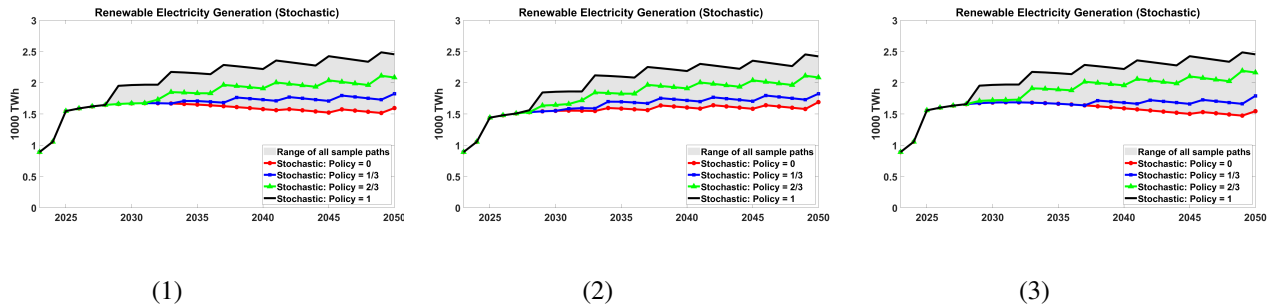
Figure 35: Renewable Electricity Generation
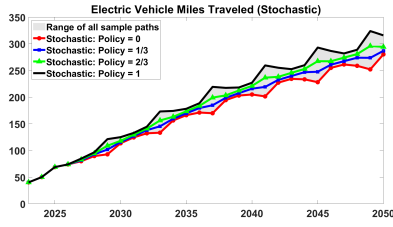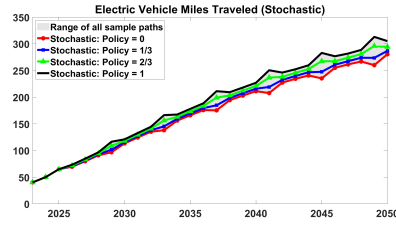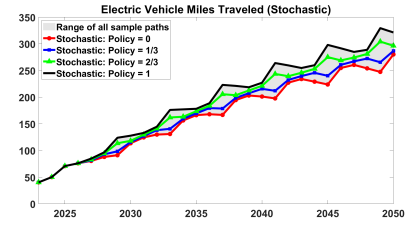
(1)　　　　　　　　　　　　(2)　　　　　　　　　　　　(3)

Figure 36: Electric Vehicle Miles Traveled
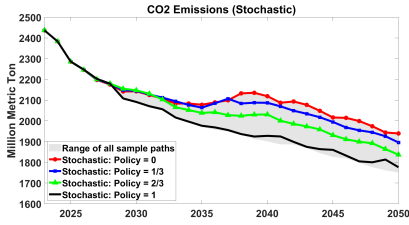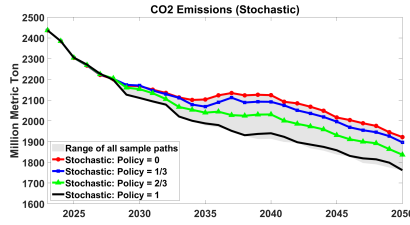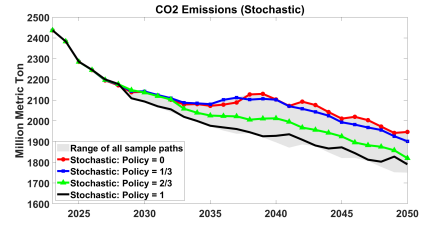
(1)　　　　　　　　　　　　(2)　　　　　　　　　　　　(3)

Figure 37: CO_2 Emissions
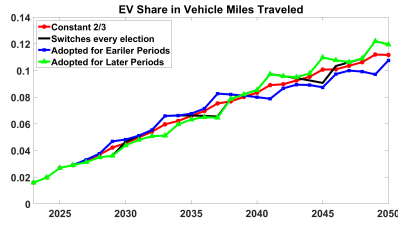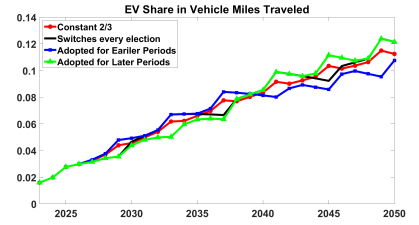
E.2　Effects of Timing
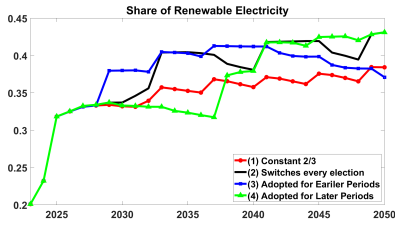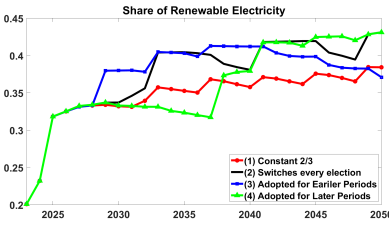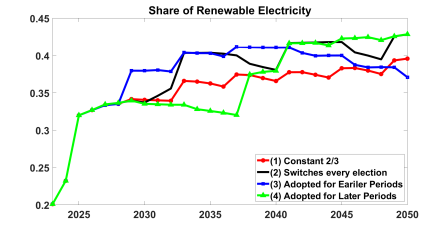
(1)　　　　　　　　　　　　(2)　　　　　　　　　　　　(3)

Figure 38: Share of Renewable Electricity Generation
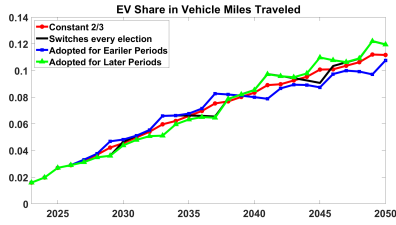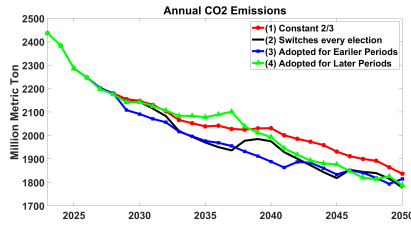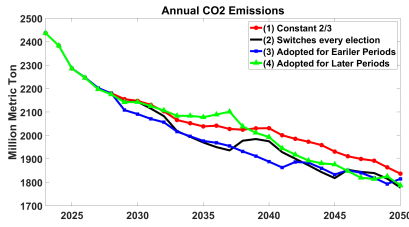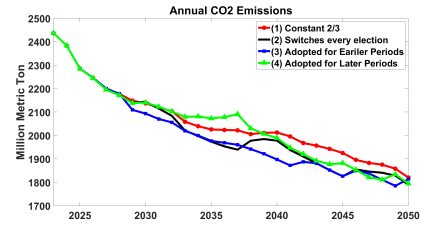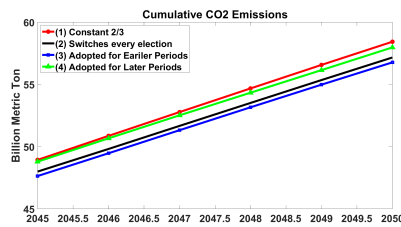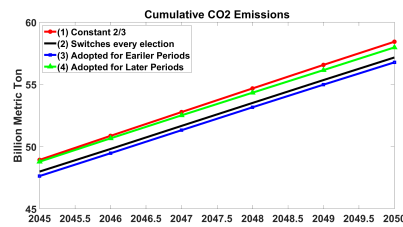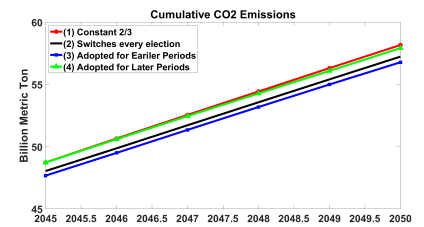
Figure 39: Share of Electric Vehicle Miles Traveled

Figure 40: Annual CO$_2$ Emissions

Figure 41: Cumulative CO$_2$ Emissions