The Systemic Risk of Climate Policy (Preliminary)

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Abstract

While the U.S. does not currently have a federal climate policy, there is widespread understanding that a carbon price may be established in the future. The uncertainty surrounding if and when a carbon price will be imposed introduces risk into the decision to invest in long-lived capital assets that are used in conjunction with fossil fuels. To understand how the macroeconomy responds to this climate policy risk, we develop a quantitative model that includes investment in long-lived, sector-specific assets such as coal power plants or wind farms. Using the observed internal carbon prices firms voluntarily levy on themselves, we infer firms' beliefs about the likelihood of a future carbon tax. We find that the risk of a future policy distorts investments towards a cleaner mix of capital, driving down U.S. carbon emissions. The emissions reduction caused by climate policy risk are equivalent to the reduction that would be achieved by imposing a carbon tax of \$3.21/ton of CO_2. Importantly, however, the non-environmental welfare costs incurred by achieving the emission reductions through the threat of a future policy are twice as large as the costs incurred by simply using the equivalent tax policy. More generally, our results demonstrate that, by ignoring the impacts of climate policy risk, existing studies have overstated both the welfare costs and emissions reductions resulting from a carbon tax policy.

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1 Introduction

Economists have developed a wide range of general equilibrium models to explore the impacts of adopting a carbon tax.[1] Using these models, the effects of taxing carbon are determined by comparing two distinct states of the world – one with a carbon tax in place and one in which agents proceed as if there will never be a carbon tax. In practice however, the current state of the world does not fit either of the above descriptions. While the U.S. does not currently have a federal climate policy, there is widespread awareness that a climate policy could be adopted at some point in the future.[2] The resulting uncertainty surrounding if and when a climate policy will be imposed introduces risk into the decision to invest in long-lived capital assets that are used in conjunction with fossil fuel. Our goal in this paper is to quantify how this climate policy risk affects investment, carbon emissions, and welfare.

To study the macroeconomic effects of climate policy risk, we design a quantitative, general equilibrium model in which a final good is produced from labor and three types of capital: (1) dirty capital that is specialized to use fossil fuel (e.g., a coal boiler or an internal combustion engine), (2) clean capital that is specialized to substitute for dirty capital or fossil fuel (e.g., a solar panel or a regenerative breaking system), and (3) non-energy capital that is not directly related to fossil fuel (e.g., a factory building). All capital is sector-specific; dirty capital cannot be sold and costlessly transformed into clean capital.[3] This friction creates the potential for some assets, particularly those used to produce dirty energy, to be stranded when a carbon tax policy is introduced. As a result, forward-looking entrepreneurs alter their investment decisions in response to the climate policy risk.

To model climate policy risk, we define a stochastic steady state in which there is a

[1] For example, see Parry et al. (1999), Rausch et al. (2011), and Williams et al. (2015).

[2] Several federal climate policy proposals were nearly adopted over the past decade (e.g., Waxman-Markey, the Clean Power Plan) and recent surveys demonstrate that a majority of U.S. adults now support increasing energy prices to combat climate change. For example, a 2016 survey completed by the Energy Policy Institute at the University of Chicago and The AP-NORC Center for Public Affairs Research found that 65% of Americans believe climate change is a problem the federal government should address and 57% would support paying higher energy bills to do so.

[3] In related work, Baldwin et al. (2019) examine how irreversibility in "dirty" and "clean" capital affects the optimal trajectory of a carbon price as well as environmental subsidies. However, the authors focus on a setting where the future policy environment in known.

small, constant probability that the government will introduce a revenue-neutral carbon tax the next period. Once the government introduces the tax, there is zero chance of returning to the "no-policy" world. Instead, all uncertainty is resolved after the introduction of the carbon tax and the economy transitions to a long-run "policy" steady state with the carbon tax in place.[4] This model of aggregate uncertainty differs from the standard approach in the macro literature in which the uncertainty is never resolved. Instead, uncertainty stems from economy-wide, stochastic shocks (e.g., TFP shocks) that are realized every period.[5] However, unlike for TFP, a climate policy shock is designed to be permanent. Our model of climate policy risk in which the uncertainty is resolved after the policy is introduced, captures this expected permanence.[6]

Analytically, we first highlight that the magnitude of the effects of climate policy risk hinge on agents' beliefs surrounding the likelihood and stringency of future climate policy. Therefore, to quantify the general equilibrium impacts of climate policy risk, we need to capture firms' beliefs regarding the level and likelihood of a future tax. To pin down the level of the potential future carbon tax, we draw from the current U.S. policy environment and assume that, if adopted, a federal carbon tax would be set at 45 dollars (in 2017 dollars) per ton of CO_2. This value is approximately equal to the EPA's estimates for the social cost of carbon (EPA 2016) and it is in line with the 40 dollar per ton tax proposed by

[4]Several theoretical papers in the environmental literature take an alternative approach to modeling the general equilibrium impacts of climate policy risk. In particular, Bretschger et al. (2018) models climate policy risk as a stochastic process that is constantly subject to change. Rezai and van der Ploeg (2018) model uncertainty over whether a climate policy will be introduced (or strengthened) at a known future date. In contrast, in our model of climate policy risk, the uncertainty arises because agents do not know if or when a climate policy will be adopted. However, conditional on being adopted, the policy is known and constant (e.g., it does not follow a stochastic process as in Bretschger et al. (2018)). Additionally, Xepapadeas (2001) and Pommeret and Schubert (2017) consider the effect of policy uncertainty on firms' investment and location decisions. However, these studies do not focus on the general equilibrium impacts of environmental policy uncertainty.

[5]For example, Kydland and Prescott (1982) and King and Rebelo (1999) explore the impact of stochastic TFP shocks in real-business cycle models. Similarly, Krusell and Smith (1998) focus on stochastic TFP shocks in a model with heterogeneity. Fernández-Villaverde et al. (2015) and Born and Pfeifer (2014) also examine general equilibrium impacts of uncertainty, however rather than stemming from stochastic TFP shocks, the uncertainty arises from stochastic policy shocks.

[6]Uncertainty surrounding the timing of future policy changes has been studied using dynamic GE models in different settings. For example, Caliendo et al. (2015) and Kitao (2018) study the impact of uncertainty surrounding future reforms to social security policies. Similarly, Kydland and Zarazaga (2016) demonstrate that anticipating future capital tax increases can explain the slow recovery following the Great Recession.

the Climate Leadership Council (Baker III et al. 2017) – a proposal that has garnered considerable support from across the political spectrum.

We provide a novel approach to infer firms' subjective probability of future climate policy from their current actions. Our approach exploits the information contained in internal carbon prices, a unique mechanism being used by firms throughout the U.S. and internationally to voluntary reduce their carbon emissions. A key reason why firms establish an internal carbon price is to distort their investment decisions to reduce future levels of fossil-fuel consumption (Ahluwalia (2017)). However, there are additional factors that may motivate the use, and level, of internal carbon prices – e.g., the desire to differentiate products as being environmentally friendly or the private benefits from warm glow. To account for these ulterior motives, we conservatively adjust the observed internal carbon price downward. Using our model, we solve for the subjective probability of adopting a carbon tax that would rationalize a profit-maximizing firm's decision to impose the adjusted internal carbon price on itself. The result implies that firms' are behaving as though they believe there is a 50 percent chance of a federal carbon tax being adopted within the next eight years.

We use the calibrated model to quantify the effects of climate policy risk on the macroeconomy. Specifically, we compare outcomes in the stochastic steady state to the corresponding outcomes in a deterministic steady state in which there is no climate policy and, critically, no risk of future climate policy. Our results reveal that the risk of climate policy alone causes reductions in emissions, even though there is no actual climate policy in place. The policy risk increases the expected return to clean capital investment and decreases the expected return to dirty capital investment, shifting the economy towards cleaner production and lower carbon emissions. Emissions are 1.15 percent lower in the stochastic steady state compared to the no-tax deterministic steady state. For comparison, the actual introduction of the carbon tax would reduce emissions by 15 percent relative to the no-tax deterministic steady state. Thus, eight percent of the total decrease in emissions from the carbon tax is achieved simply by forward-looking firms internalizing the risk of future climate policy.

While the risk of climate policy acts like an actual climate policy in the sense that it reduces emissions, it is far more costly. The decrease in emissions in the stochastic steady state is equivalent to what would be achieved in a deterministic steady state with a carbon tax equal to 3.21 dollars per ton. However, the non-environmental welfare cost of the stochastic steady state (relative to the deterministic deterministic steady state) is more than double the welfare cost from levying a \$3.21/ton tax on carbon emissions. Climate policy risk is more costly than actual climate policy because it results in capital misallocation. Since entrepreneurs must choose capital before they know whether the government will introduce the policy, they have too much clean capital and too little dirty capital if government does not introduce the tax, and the reverse if the government does introduce the tax. This misallocation reduces the expected return to capital, resulting in a lower aggregate capital stock. Lower total capital reduces output and consumption, generating the large costs from carbon emissions reduced through climate policy risk. In contrast, there is no uncertainty in a deterministic steady state with the \$3.21/ton carbon tax, and thus, entrepreneurs can attain the optimal allocation of capital for the known policy environment.

The results of our analysis also have important implications with regards to evaluating the impacts of climate policies. To predict the macroeconomic impacts of adopting a carbon tax, the existing literature implicitly assumes that we are starting from a state of the world where there is no climate policy risk. However, given that forward-looking firms are making investments with an understanding that a future carbon price is a real possibility, then such a comparison could misrepresent the true effects of introducing a carbon tax. In particular, we find that failing to account for the effects of policy risk overstates the welfare cost incurred, and emission reductions achieved, by adopting a carbon tax.

2 Climate policy risk

Firms' investment decisions are always made with an eye towards an uncertain future. This uncertainty stems from unknown future demand as well as unknown future production costs. The economics literature has long-studied how profit-maximizing firms' investment responds to these various sources of uncertainty (e.g., Lucas and Prescott (1971), Abel (1983), Dixit et al. (1994)). In this analysis, we build on this large literature to examine how uncertainty surrounding future climate policy, which can affect both production costs and demand, affects the level and composition of the capital assets.

Intuitively, for the risk of a future climate policy to meaningfully affect current investment decisions, two conditions must be met. First the likelihood of a federal climate policy being adopted in the near future – i.e. in a period of time that is shorter than the lifespan of the capital investments – cannot be trivially small. While there is no way to directly measure the probability of a U.S. carbon policy, there is certainly anecdotal evidence suggesting that the probability is not fleetingly small. For one, recent surveys demonstrate that a majority of U.S. adults now support increasing energy prices to combat climate change.[7] Additionally, several federal climate policy proposals were nearly adopted over the past decade (e.g., Waxman-Markey, the Clean Power Plan). This broad base of public support suggests that there is widespread awareness that a federal climate policy could be adopted in the near future. This is also a view expressed within many industries. For example, the Director of Sustainability at The Dow Chemical Company noted, "It's very difficult to predict the future, obviously, but we need to look at the probabilities. With external carbon prices, it's only a matter of time. (WBCSD 2015)"

The second condition that must be met for climate policy risk to meaningfully affect present investment decisions is that firms must believe the climate policy, if implemented, will be stringent enough to alter the returns to different types of capital. Again, there is no way to measure this subjective belief. However, all signs suggest that, if implemented, a climate policy would indeed have significant consequences for the returns to different types of capital. Looking towards other regions of the world for insights, the European Union's Emission Trading Scheme has established a price on carbon emissions that, as of 2019, has hovered around 25 Euros (or 27 USD) per ton of CO_2. At this price, there is already clear evidence that fossil-fuel intensive capital, such as a coal-fired electricity generator, is

[7]For example, a 2016 survey completed by the Energy Policy Institute at the University of Chicago and The AP-NORC Center for Public Affairs Research found that 65% of Americans believe climate change is a problem the federal government should address and 57% would support paying higher energy bills to do so.

experiencing a dramatic reduction in profitability (IEEFA 2019). Policy proposals that are garnering the greatest support in the U.S. currently call for even stronger actions to reduce emissions. For example, the proposal put forth by the Climate Leadership Council (CLC) calls for a CO_2 tax on carbon emissions set at 40 dollars per ton (Baker III et al. 2017). The Green New Deal and the leading democratic presidential candidates support US carbon neutrality by 2050. Such a goal would require far more dramatic reductions in emissions than what would be achieved with the CLC's proposed 40 dollar per ton tax.

The combination of growing public support combined with the current policy proposals suggest that both the likelihood and expected stringency of a future U.S. climate policy are large enough to impact firms' investment decisions. Indeed, empirical evidence demonstrates that firms do respond to this climate policy risk. In particular, focusing on the resource extraction sector, Lemoine (2017) finds that coal extraction increases, and prices are depressed, in response to an expected future climate policy. Barnett (2018) provides theoretical and empirical evidence of a similar effect in the oil market in response to changes in the expectation of future climate policies. These findings are consistent with prior theoretical work studying how fossil fuel resource extraction responds to the threat of future environmental policies.[8]

However, the resource extraction sector represents a relatively small piece of the macroeconomy. There are many types capital that use fossil fuel and are not involved in the resource extraction, such as an internal combustion engine or a coal boiler. Similarly, there exist many other types of capital that are specifically designed to replace the fossil-fuel-using capital, and thus would also be affected by climate policy risk. While there is no direct empirical evidence on how climate-policy risk affects investment in any of these types of energy-related capital, there is ample anecdotal evidence demonstrating that firms across a wide range of industries adjust investment in response to climate policy risk.

Perhaps the clearest evidence that firms are taking the threat of future climate policies

[8]For example, Sinn (2008) initial work on the "Green Paradox" builds on the Hotelling Model of resource extraction to highlight that carbon intensive energy sources will experience increased rates of extraction in response to an expected future climate policy.

seriously is the fact that a large number of firms have begun using internal carbon prices. There are two broad types of internal carbon price instruments – the most common being an internal "carbon shadow price". Firms use these shadow prices primarily to evaluate the returns or net-present value of long-lived investments under different scenarios with future carbon taxes in place (Ahluwalia 2017). For example, to guide long-term capital investment decisions, Shell uses a shadow price of $40/ton of CO_2 – which has reportedly resulted in the decision to pass on many potential CO_2-intensive investment opportunities.

The second type of internal carbon price is a carbon fee. In contrast to the shadow price, the carbon fee is actually a tax on the firm's direct emissions (or emissions embodied in its energy use). The revenue raised by this internal tax can be transfered within the organization or, in some cases, used to pay for emission offsets or renewable energy credits. For example, Microsoft imposes an internal carbon fee of $10/ton of CO_2 on the emissions resulting from its energy use – with the revenue being used to purchase carbon offsets and renewable energy credits.

The use of internal carbon prices has become widespread. In a recent survey of nearly 5,000 firms performed by CDP (formerly Carbon Disclosure Project), 517 firms reported using internal carbon prices and another 732 have plans in place to adopt internal prices within two years. Notably, over half of the surveyed firms in the energy sector, which are the most exposed to climate-policy risk, were using internal carbon prices. Similarly, 35 percent of firms in the materials sector and 23 percent of firms in the industrial sector reported the use of internal carbon prices. Many of these firms are either located in the U.S. or do business in the U.S.

Internal carbon prices are only one of many tools firms can use to alter investment decisions in response to climate policy risk. Instead of using a carbon price, some firms choose to set their own internal emissions targets. For example, Walmart launched Project Gigaton in 2017 to reduce emissions throughout its supply chain. The company reduced emissions by 6.1 percent in 2017 and plans to reduce its scope 1 and 2 emissions by 18 percent by 2025 and purchase 50 percent of its electricity from renewable sources (Walmart

2017). Similarly, Kroeger's 2020 sustainability goals include reducing electricity consumption by 40 percent from a year 2000 baseline. To meet the target, the company invests in energy efficient features in both new and existing stores (Kroger 2019). Likewise, Mars Inc.'s climate action plan includes reducing greenhouse gas emissions across its value chain by 27 percent by 2025 and by 67 percent by 2050 (Mars 2018).

Yet another alternative to an internal carbon price is for firms to voluntarily adopt stricter regulations than those imposed by the federal government. For example, automakers Ford, Honda, Volkswagen, and BMW choose to adopt California's stricter fuel economy standards, which require an average fuel economy for new cars and trucks equal to 54.5 miles per gallon, instead of the laxer regulations proposed by President Trump (Holden 2019). Transportation is responsible for 29 percent of US carbon emissions, and thus the fuel economy standards represent an important form of climate policy. Reportedly, "the companies are worried about years of regulatory uncertainty that could end with judges deciding against Trump" and implementing the stricter standards. Similarly, BP, Shell, and Exxon Mobil were among several major oil and gas companies to oppose President Trump's rollback of methane regulations. Shell even went so far as to pledge that "while the law may change in this instance, our environmental commitments will stand" (Krauss 2019).

There are certainly many possible reasons why firms might want to reduce their carbon emissions using an internal carbon price or other company policy. To some degree, firms may be motivated by a desire to differentiate their product(s) as being "green" or to mitigate reputation risks. The use of the internal carbon fees to raise revenues for pro-social or pro-environmental objectives may also be motivated in part by a belief in corporate social responsibility. However, surveys of firms that are using internal carbon prices find that the "single largest motivation for adopting a shadow price is to better understand and anticipate the business risks from existing or expected carbon regulations and shift investments toward projects that would be competitive in a carbon-constrained future (Ahluwalia (2017))." Effectively, firms are responding to the threat of a future climate policy by electing to distort their current capital portfolios. This is exactly the behavior we seek to model in this analysis.

Ultimately, our objective is to quantify how the level and composition of capital investment is affected by the type of climate policy risk we have described above. Specifically, firms believe that, at some point in the future, an environmental policy will establish a price on carbon emissions. However, firms are uncertain as to when the policy may be adopted. In order to quantify the effects of this resulting uncertainty, we ultimately need to calibrate the fundamentally unobservable beliefs firms have surrounding the likelihood of future climate policy. To do so, we utilize the one quantifiable piece of information we have available – the internal carbon fees publicly reported by firms. Among the firms that publicly report their internal carbon fees, there is a modal price of 10 dollars per ton of CO_2. This is also consistent with the average carbon fee reported by firms surveyed by the World Business Council for Sustainable Development (WBCSD 2015).

It is important to stress that there is a very small sample of internal carbon fees that we are able to observe.[9] While there are a much larger number of firms reporting internal carbon prices, these are typically shadow prices. The shadow price only contains information surrounding the firms' expected level of the tax. It provides no information on the probability that the firm places on whether the government will introduce the tax. For example, suppose a firm evaluates the profitability of an investment opportunity under two scenarios, one with a shadow carbon price of zero and one with a shadow carbon price of 45. Whether or not the firm chooses to undertake that investment depends on the probabilities the firm places on each scenario, which we do not observe.

In contrast, the carbon fee determines how firms actually allocate investment in the face of climate policy risk. Unlike the shadow price, there is no additional probability analysis. Firms simply make investments as though there was a carbon tax equal the internal carbon fee. The level that firms choose for the fee contains information on both the probability and level of the expected tax. As a result, we can use the internal carbon fee to calibrate firms' subjective probability of this tax. While the modal carbon fee is 10 dollars per ton of CO_2,

[9] We have information on the level of the internal carbon fee for the following companies: Walt Disney, Microsoft, Phillip Morris, Ben and Jerry's, and Google.

this price level may be motivated by more than simply climate policy risk. For example, "green-washing" or warm-glow motives may inflate the carbon fee relative to the level the firm would set purely to address the climate policy risk. To address this concern, we use two approaches. First, we conservatively deflate the observed carbon fees, effectively assuming that only a portion of the fee is motivated by climate policy risk. In addition we explore how the quantitative impacts vary using a wider range of internal carbon fees. In each case, we back out what firms' beliefs about a future carbon tax must be in order to rationalize the voluntary use of a given internal carbon fee. With these calibrated beliefs, we explore how capital investment responds to climate policy risk.

3 Model

We build a simple dynamic model to understand how the risk of future climate policy affects entrepreneurs' investment decisions. The model is intentionally stylized to allow us to provide an analytical characterization of the effect of climate policy risk on the equilibrium levels of clean and dirty capital and carbon emissions. In particular, we focus only on the production-side of the economy; we take the interest rate and labor supply as exogenous. We abstract from the allocation of labor across the clean and dirty sectors, non-energy related capital, and any investment frictions. We relax all of these assumptions in Section 4 to follow. We relegate all proofs to Appendix A.

3.1 Environment

The economy is comprised of infinitely-lived entrepreneurs and workers. There is a unique final good, y, that is produced competitively from a clean intermediate input, x^c, a dirty intermediate input, x^d, and labor, l. The final-good production function is a Cobb-Douglas aggregate of the two intermediate inputs and labor,

$$y = (x^c)^\gamma (x^d)^\theta l^{1-\gamma-\theta}. \tag{1}$$

Parameters γ and θ denote the factor shares of the clean and dirty intermediates, respectively. We normalize labor supply to unity. The final good is the numeraire.

The clean intermediate is produced competitively from clean capital, k^c. The dirty intermediate is produced competitively from dirty capital, k^d, and fossil fuel, f. Both production functions feature constant returns to scale and are given by,

$$x^c = k^c \quad \text{and} \quad x^d = \min[k^d, f] \tag{2}$$

Fossil fuel is produced from units of final good at constant marginal cost, ζ.

Dirty capital refers to any capital that is specialized to use fossil fuel. Examples include capital used in fossil fuel extraction, such as an oil rig, capital used to produce electricity from fossil fuels, such as a coal boiler, and capital that requires fossil fuel to operate, such as an internal combustion engine or a polymerisation reactor to manufacture plastics.

Clean capital refers to any capital that preforms the same function as the dirty capital, but does not use fossil fuel. Examples include capital used to produce electricity from non-fossil sources, such as a wind turbine or a nuclear reactor, capital that increases energy efficiency, such as regenerative brakes in hybrid vehicles, and capital that allows for an alternative production process that does not use fossil fuel, such as the fermentors used to make bioplastics.

The Leontief production function for the dirty intermediate implies that there is no substitutability between dirty capital and fossil fuel. For example, a given internal combustion engine or coal boiler each require specific quantities of fossil fuel to operate. In practice, firms can reduce fossil fuel consumption by switching to non-carbon emitting (clean) energy sources or by improving energy efficiency. We model both of these channels as part of clean capital. Thus any reduction in the carbon intensity of the final good must be achieved by substituting the clean intermediate for the dirty intermediate, and not by substituting dirty capital for fossil fuel.

3.2 Climate policy risk

We study a stochastic steady state designed to capture the climate policy risk faced by US firms, described in Section 2. In the stochastic steady state, there is no carbon tax, but each entrepreneur expects that the government will introduce a carbon tax, τ, with probability, ρ, next period. All uncertainty is resolved after the carbon tax is introduced; the economy leaves the stochastic steady state and transitions to a deterministic steady state with the carbon tax in place.

This model of climate policy risk is differs from the standard approach to modeling aggregate uncertainty in the macro literature. In the standard approach, there exists an economy-wide shock, often to TFP, that realizes every period. The uncertainty is typically never resolved; after each realization of the aggregate shock, agents still must form expectations over the future realizations of the shock. In equilibrium, aggregate variables are never constant; instead, they continually evolve in response to the realization of the aggregate shocks.

In contrast, in our model of climate policy risk, the realization of the carbon tax is an absorbing state. Once the government introduces the tax, there is zero probability of transitioning back to the state of the world in which there is no carbon tax. We study the long-run equilibrium (stochastic steady state) before the economy transitions to this absorbing state; there is no carbon tax in place but agents expect the government to introduce a carbon tax in the future. As discussed in Section 2, such an equilibrium is well-suited to describe the US economy; there is no federal climate policy, yet firms' actions indicate that they expect the government to introduce a climate policy in the future. Aggregate variables are constant in this equilibrium because the realization of the aggregate shock, the carbon tax, has, historically, always been zero.

3.3 The stochastic steady state

The representative final-good entrepreneur chooses the clean and dirty intermediates and labor to maximize profits, taking prices as given. The entrepreneur makes all decisions at the start of the period, after she learns if the government introduced the climate policy. The first order conditions imply the following expressions for the price of the clean, p^c, and dirty, p^d, intermediates, respectively,

$$p^c = \gamma(x^c)^{\gamma-1}(x^d)^{\theta} \quad \text{and} \quad p^d = \theta(x^c)^{\gamma}(x^d)^{\theta-1}. \tag{3}$$

The representative clean entrepreneur chooses investment in next period's level of clean capital to maximize the expected present discounted value of future profits. She makes her investment decision before she learns whether the government will introduce the tax next period, implying that her expectations of future climate policy affect her current investment. Let $V^c(k^c;0)$ denote the clean entrepreneur's value function in the stochastic steady state without a carbon tax, and $V_t^c(k^c;1)$ denote her value function in period t of the transition after the government introduces the carbon tax. The clean entrepreneur's value function in the stochastic steady state equals,

$$V^c(k^c;0) = \max_{(k^c)'} \left\{ p^c k^c - i^c + \left(\frac{1}{1+r}\right) \left[\rho V_1^c((k^c)';1) + (1-\rho)V^c((k^c)';0)\right] \right\} \tag{4}$$

subject to the law of motion for clean capital,

$$(k^c)' = (1-\delta)(k^c) + i^c. \tag{5}$$

Parameter r denotes the exogenous interest rate and parameter δ is the depreciation rate. The entrepreneur's flow profits, $p^c k^c - i^c$, equal the total revenue from production, $p^c k^c$, minus investment expenses, i^c. The continuation value in equation (4) is a weighted average of the continuation value if the government does not introduce the carbon tax and the economy remains in the stochastic steady state, $V^c((k^c)';0)$, and the continuation value if the government does introduce the carbon tax and the economy is in the first period of the transition, $V_1^c((k^c)';1)$. The weights, ρ and $1-\rho$, are equal to the probability that the government does, and does not introduce the carbon tax in the next period.

The clean entrepreneur's value function in period t of the transition equals,

$$V_t^c(k^c;1) = \max_{(k^c)'} \left\{ p^c k^c - i^c + \left(\frac{1}{1+r}\right) V_{t+1}^c((k^c)';1) \right\} \tag{6}$$

subject to the law of motion for clean capital (equation (5)). Since all uncertainty is resolved after the introduction of the carbon tax, the continuation value in period t of the transition simply equals the value function in period $t+1$ of the transition.

The representative dirty entrepreneur chooses of fossil fuel and investment in next period's level of dirty capital to maximize the expected present discounted value of future profits. Like the clean entrepreneur, she chooses investment before she learns whether the government will introduce the tax next period. Using notation parallel to that for the clean entrepreneur, the dirty entrepreneur's value function in the stochastic steady state equals,

$$V^d(k^d;0) = \max_{(k^d)',f} \left\{ p^d k^d - \zeta f - i^d + \left(\frac{1}{1+r}\right) \left[\rho V_1^d((k^d)';1) + (1-\rho) V^d((k^d)';0)\right] \right\} \tag{7}$$

subject to the law of motion for dirty capital,

$$(k^d)' = (1-\delta)(k^d) + i^d, \tag{8}$$

and the Leontief constraint that the dirty intermediate producer purchase sufficient fossil fuel to operate the dirty capital, $f \geq k^d$. The dirty entrepreneur's flow profits, $p^d k^d - \zeta f - i^d$, equal her total revenue, $p^d k^d$ minus her expenses on fossil fuel, ζf, and investment, i^d. Since there is no carbon tax in the stochastic steady state, the entrepreneur only pays the extraction cost, ζ, for each unit of fossil fuel.

The value function for the dirty entrepreneur in the first period of the transition equals

$$V_1^d(k^d;1) = \max_{(k^d)',f} \left\{ p^d k^d - (\zeta+\tau) f - i^d + \left(\frac{1}{1+r}\right) V_2^d((k^d)';1) \right\} \tag{9}$$

subject to the law of motion for dirty capital, equation (8), and the Leontief constraint. With the carbon tax in place, the dirty entrepreneur must pay the extraction cost, ζ, plus the tax, τ, for each unit of fossil fuel.

We define a *stochastic steady state* for this economy as a set of prices for the clean and dirty intermediate and labor, $\{p^c, p^d, w\}$, allocations for clean and dirty entrepreneurs, $\{k^c, k^d, f\}$, and allocations for the final good entrepreneur, $\{x^c, x^d, l\}$, such that given an exogenous interest rate, r, and a probability, ρ, of a carbon tax, τ, next period, the following conditions hold:

1. Given prices, the final good entrepreneur chooses clean and dirty intermediates and labor to maximize profits.

2. Given prices, the clean and dirty entrepreneurs solve the expected-profit maximization problems described by the value functions in equations (4) and (7).

3. The markets for labor and the clean and dirty intermediate inputs clear.

3.4 The aggregate effects of climate policy risk

We analytically characterize how climate policy risk affects the level and composition of clean and dirty capital in the stochastic steady state and the resulting implications for output and emissions.

Proposition 1. *Climate policy risk increases the ratio of clean to dirty capital and decreases the aggregate capital stock. The ratio of clean to dirty capital, K^c/K^d, in the stochastic steady state is increasing in both the probability, ρ, and size, τ, of the carbon tax. Conversely, the aggregate level of capital in the stochastic steady state is decreasing in both the probability and the size of the carbon tax.*

Proposition 1 demonstrates that climate policy risk distorts the level and composition of capital away from what would prevail in a deterministic steady state with no carbon tax. The ratio of clean to dirty capital in the stochastic steady state equals,

$$\frac{K^c}{K^d} = \left(\frac{\gamma}{\theta}\right)\left(\frac{1 + r + \zeta + \rho\tau}{r + \delta}\right). \tag{10}$$

First, observe that if the probability of a tax and the fossil fuel extraction cost both equal zero, $\rho = \zeta = 0$, then the ratio of clean to dirty capital simply equals the ratios of the factor shares, γ/θ. A positive price of fossil fuel, $\zeta > 0$, raises the operating costs of dirty capital, increasing the ratio of clean to dirty capital. Similarly, the possibility of a future carbon tax, $\rho > 0$, raises the expected operating costs of dirty capital next period, further increasing the ratio of clean to dirty capital. The increase in the ratio of clean to dirty capital shifts the economy towards cleaner production. In equilibrium, fossil fuel use equals the level of dirty capital, implying that the simple risk of future climate policy decreases the carbon intensity of output.

Even though climate policy risk increases the ratio of clean to dirty capital, the levels of both types of capital fall. The levels of clean and dirty capital in the stochastic steady state equal,

$$K^c = \left(\frac{\gamma}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}} \left(\frac{r+\delta}{1+r+\zeta+\rho\tau}\right)^{\frac{\theta}{1-\gamma-\theta}} \left(\frac{\theta}{\gamma}\right)^{\frac{\theta}{\gamma}} \tag{11}$$

$$K^d = \left(\frac{\gamma}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}} \left(\frac{r+\delta}{1+r+\zeta+\rho\tau}\right)^{\frac{1-\gamma}{1-\gamma-\theta}} \left(\frac{\theta}{\gamma}\right)^{\frac{1-\gamma}{\gamma}} \tag{12}$$

The expressions for K^c and K^d are both decreasing in the probability, ρ, and the size, τ, of the carbon tax.

The aggregate capital stock falls because the climate policy risk implies that the economy does not attain the allocation of capital that would be optimal ex-post, after the uncertainty is resolved. If the government does not introduce the tax, then the economy has too much clean capital and too little dirty capital; the realized marginal product of clean capital is greater than that of dirty capital. Conversely, if the government does introduce the carbon tax, then the economy has too little clean capital and too much dirty capital; the realized marginal product of clean capital is less than that of dirty. This misallocation reduces the expected marginal products of both clean an dirty capital, causing entrepreneurs to demand less capital.

The results from Proposition 1 imply that the risk of climate policy reduces both output and emissions. Output falls because the climate policy risk decreases the capital stock. Emissions fall because of both the fall in output and the shift towards cleaner capital. Thus, climate policy risk creates costs from the decrease in output and benefits from the reduction in emissions that are qualitatively similar to those created by the actual tax.

In this simple setting, the macro-implications from the climate-policy risk are equivalent to a less stringent version of the climate policy itself. In particular, a deterministic steady state with carbon tax $\tilde{\tau} = \rho\tau$ is identical to the stochastic steady state. This equivalence stems partially from the fact that the only way to reduce carbon emissions in the analytic model is through changes in level and composition of the capital stock, which must be decided before entrepreneurs know whether the government will introduce the carbon tax. If entrepreneurs have other ways to adjust production after the uncertainty is resolved, such as by changing more flexible inputs like labor, then the stochastic steady state is no longer equivalent to a deterministic steady state with a less-stringent version of the climate policy. The quantitative model we develop in Section 4 incorporates these additional channels.

4 Quantitative model

We develop a richer, general equilibrium model to quantify the effects of climate policy risk on the US economy. The quantitative model differs from the analytic model on several dimensions. First, we allow for the allocation of labor across the different intermediate input sectors, providing entrepreneurs with a mechanism to adjust production after they learn whether the government introduced the carbon tax. Second, we include a non-energy-related capital, since much of the US capital stock is not directly related fossil fuel. Third, we model investment as partially irreversible, to capture the potential losses from selling dirty capital. And fourth, we model the household-side of the economy which allows us to analyze the full, general equilibrium effects of climate policy risk. We assume that when the carbon tax is introduced, all revenue is returned back to the household through equal lump-sum transfers.

4.1 Labor and non-energy capital

We model the allocation of labor across the different intermediate sectors. Unlike capital, each entrepreneur hires labor after the realization of the tax. This additional flexibility allows each entrepreneur to adjust her production in response to the tax, partially mitigating the effects of climate policy risk. The labor-market is perfectly competitive; all entrepreneurs pay the market wage, w.

The production functions for the clean and dirty intermediate input equal,

$$x^c = A^c(k^c)^\alpha(l^c)^{1-\alpha} \quad \text{and} \quad x^d = A^d \min[(k^d)^\alpha(l^d)^{1-\alpha}, \mu f]. \tag{13}$$

Variables l^c and l^d denote labor hired by the clean and dirty entrepreneurs, respectively. Parameter α denotes capital's share, and parameters A^c and A^d denote total factor productivity in clean and dirty production. Leontief parameter μ determines fossil energy's share of dirty-intermediate production.

The majority of capital used in most production processes is not directly related to energy. For example, tee-shirts are produced using factory buildings, sewing machines, lights, assembly lines, etc. While this capital all requires electricity to operate, it does not require that the electricity be made from fossil fuel. We classify this type of capital as non-energy, since it is not specialized to use fossil fuel (dirty) or to replace fossil fuel (clean).[10]

To incorporate non-energy capital, we introduce a non-energy intermediate input, x^n. The non-energy intermediate is produced competitively from non-energy capital, k^n, and labor, l^n, according to the Cobb-Douglas production function,

$$x^n = A^n(k^n)^\alpha(l^n)^{1-\alpha} \tag{14}$$

Parameter A^n denotes total factor productivity in non-energy production.

[10] If the factory buildings and machines embody energy efficiency, then we would classify one portion of the buildings and machines as clean capital and the other portion as non-energy capital.

The final good is a CES aggregate of the non-energy, clean, and dirty intermediate inputs,

$$y = \left((x^e)^{\frac{\phi-1}{\phi}} + (x^n)^{\frac{\phi-1}{\phi}} \right)^{\frac{\phi}{\phi-1}} \quad \text{where} \quad x^e = \left((x^c)^{\frac{\varepsilon-1}{\varepsilon}} + (x^d)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}. \tag{15}$$

Parameter ε denotes the elasticity of substitution between the clean and dirty energy intermediates. Parameter ϕ denotes the elasticity of substitution between the composite of energy-related intermediates x^e, and the non-energy intermediate, x^n.

4.2 Partially irreversible investment

Proposition 1 demonstrates that the introduction of climate policy could result in a decrease in demand for dirty capital. This fall in demand could be extremely costly if the entrepreneur cannot recover the full value of capital that she re-sells. This loss in value could result from the transactions and physical costs of re-sale and from the buyer's potential concerns that the used capital is a "lemon" (Bloom 2009). These losses are exacerbated if the entrepreneur sells the used capital across sectors (Ramey and Shapiro 1999). For example, suppose a dirty entrepreneur sells a used coal boiler to a clean entrepreneur. The clean entrepreneur's valuation of the boiler's parts is likely considerably less than the value of the boiler.

To incorporate the losses from resale, we model an asymmetric adjustment cost on investment,

$$G(i) = \frac{\lambda}{2} \left[-i + (i^2 + \eta)^{\frac{1}{2}} \right], \tag{16}$$

where variable i denotes the entrepreneur's level of investment. For small values of η, the adjustment cost function, $G(i)$, provides a twice-differentiable approximation to the piecewise adjustment-cost function, H,

$$H(i) = \begin{cases} 0 & : i \geq 0 \\ |\lambda i| & : i < 0 \end{cases} \tag{17}$$

Parameter $\lambda \in [0, 1]$ equals the fraction of the capital stock the entrepreneur looses from re-sale. At the extremes, $\lambda = 1$ corresponds to perfectly irreversible investment and $\lambda = 0$ corresponds to perfectly reversible investment.

Unlike capital, labor is fully fungible across the different sectors. The absence of any type of labor adjustment costs makes sense, given the broad nature of the different sectors. For example, the skills of a chemist or a construction worker could be combined with all three types of capital, and thus used in all three sectors.

4.3 Households

The economy is inhabited by a continuum of infinitely-lived, identical households, comprising workers and entrepreneurs. The worker in each household is endowed with one unit of time which she can divide between labor and leisure. The worker can supply labor to any entrepreneur, not just the ones in her household. Each period, the household receives utility from consumption, c, and dis-utility from hours worked, h. The per-period utility function is,

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} - \chi \frac{h^{1+\frac{1}{\theta}}}{1+\frac{1}{\theta}}, \tag{18}$$

where parameter σ is the coefficient of relative risk aversion, parameter χ measures the dis-utility from hours, and parameter θ is the Frisch elasticity of labor supply.

4.4 The stochastic steady state

The representative final-good entrepreneur chooses the clean, dirty, and non-energy intermediates to maximize profits, taking prices as given. Like in the analytic model, the final-good entrepreneur makes all decisions at the start of the period, after she leans if the government introduced the climate policy. To simplify the notation, we do not write the final good entrepreneur's problem as part the household optimization.[11]

[11] The final good entrepreneur maximizes flow demands for intermediate inputs within a time period, implying that the profit-maximizing allocation is equivalent to the utility-maximizing allocation.

The clean, dirty, and non-energy entrepreneurs and workers in each representative household make decisions to maximize the household's expected, present discounted value of lifetime utility, taking prices as given. The clean entrepreneur chooses clean-capital investment and clean-labor demand, the dirty entrepreneur chooses dirty-capital investment, dirty-labor demand, and fossil fuel, and the non-energy entrepreneur chooses non-energy capital investment and non-energy labor demand. The collective investment decisions by all three entrepreneurs' determine the household's level of saving. The worker chooses hours of labor supply. The entrepreneurs and the workers all make decisions subject to the same household budget constraint,

$$c_t = w_t h_t + \pi_t^n + \pi_t^d + \pi_t^c. \tag{19}$$

Household income includes labor income, $w_t h_t$, and the flow profits from the clean, dirty, and non-energy entrepreneurs, denoted by π^c, π^d, and π^n, respectively,

$$\pi_t^c = p_t^c x_t^c - w_t l_t^c - i_t^c - G(i_t^c) \tag{20}$$

$$\pi_t^d = p_t^d x_t^d - \zeta f_t - w_t l_t^d - i_t^d - G(i_t^d) \tag{21}$$

$$\pi_t^n = p_t^n x_t^n - w_t l_t^n - i_t^n - G(i_t^n) \tag{22}$$

We write the optimization problem for the entrepreneurs and workers in the stochastic steady state as a single household value function. Let $V(k^c, k^d, k^n; 0)$ denote the household's value function in the stochastic steady state without a carbon tax, and $V_t(k^c, k^d, k^n; 1)$ denote her value function in period t of the transition after the government introduces the carbon tax. The household's value function in the stochastic steady state equals,

$$\begin{aligned} V(k^c, k^d, k^n; 0) = & \max_{(k^c)', (k^d)', (k^n)', h, l^c, l^d, l^n, f} \frac{c^{1-\sigma}}{1-\sigma} - \chi \frac{h^{1+\frac{1}{\theta}}}{1+\frac{1}{\theta}} \\ & + \beta \left[\rho V_1((k^c)', (k^d)', (k^n)'; 1) + (1-\rho) V((k^c)', (k^d)', (k^n)'; 0) \right] \end{aligned} \tag{23}$$

Parameter β is the household's discount factor. If the government does introduce the carbon tax, then the household's value function in period t of the resulting transition equals,

$$V_t(k^c, k^d, k^n; 1) = \max_{(k^c)',(k^d)',(k^n)',h,l^c,l^d,l^n,f} \frac{c^{1-\sigma}}{1-\sigma} - \chi \frac{h^{1+\frac{1}{\theta}}}{1+\frac{1}{\theta}} + \beta V_{t+1}((k^c)', (k^d)', (k^n)'; 1) \quad (24)$$

The household's budget constraint over the transition includes includes the transfers, T_t, from the carbon tax revenue,

$$c_t = w_t h_t + \pi_t^n + \pi_t^d + \pi_t^c + T_t. \quad (25)$$

Similarly, the dirty entrepreneur's profits over the transition incorporate that she must pay the extraction cost, ζ, plus the carbon tax, τ, for each unit of fossil fuel,

$$\pi_t^d = p_t^d x_t^d - (\zeta + \tau) f_t - w_t l_t^d - i_t^d - g(i_t^d)$$

The expressions for the clean and non-energy entrepreneurs' profits over the transition are the same as in equations (20) and (22).

We define a *stochastic steady state* for this economy as a set of prices for the clean, dirty, and non-energy intermediates and labor, $\{p^c, p^d, p^n, w\}$, allocations for households and intermediate entrepreneurs, $\{k^c, k^d, k^n, h, c, f\}$, allocations for the final good entrepreneur, $\{x^c, x^d, x^n\}$ such given a probability, ρ, of a carbon tax, τ, next period, the following holds:

1. Given prices, the final-good entrepreneur chooses clean, dirty, and non-energy intermediates to maximize profits.

2. Given prices, the representative household maximizes the value function equation (23), subject to the budget constraints (equations (19) and (25)), the time endowment, $h \leq 1$, and the non-negativity constraints, $c \geq 0, k^c \geq 0, k^d \geq 0, k^n \geq 0$.

3. The markets for labor, clean, dirty, and non-energy intermediate inputs all clear.

5 Calibration

We calibrate the model's stochastic steady state to match the current US economy. We set the future carbon tax at 45 in 2017 dollars per ton, approximately equal to the EPA's estimates of the social cost of carbon.[12] This value of the tax is slightly higher than the 40 dollars per ton proposed by the CLC and considerably lower than what would be required to achieve the Green New Deal and democratic presidential candidates' target of carbon neutrality by 2050.

The model time period is one year. We calibrate seven parameters, $\{\alpha, \varepsilon, \phi, \lambda, \eta, \theta, \sigma\}$ directly from the data and existing literature. Given these directly calibrated parameters, we jointly calibrate the remaining seven parameters $\{\mu, A^c, A^d, \delta, \beta, \chi, \rho\}$ so that seven moments in the model match a set of seven empirical targets. All of the moments match the empirical targets up to four decimal places. Tables 1 and 2 report the parameter values that result from the direct calibration and the method-of-moments procedure, respectively.

Much of the calibration approach is standard in the macro literature. The important novelty is specifying firms' beliefs over the likelihood of the future tax. Section 5.1 details the calibration of ρ. Sections 5.2 and 5.3 discuss the calibration of the remaining parameters. Appendix B reports additional details and describes all data sources used in the calibration.

[12] Using a three percent discount rate, the EPA reports the social cost of carbon equal in 2015 equal to 42 dollars and in 2002 equal to 49 dollars (both values are in year 2017 dollars).(EPA 2016).

Table 1: Parameter Values: Direct Calibration

Stochastic	Value
Production	
Capital share: α	0.33
Clean and dirty substitution elasticity: ε	3
Energy and non-energy substitution elasticity: ϕ	0.10
Adjustment cost: λ	0.43
Perturbation parameter: η	1.0e-09
Preferences	
Frisch labor supply elasticity: θ	0.5
CRRA coefficient: σ	2

Table 2: Parameter Values: Method of Moments

Stochastic	Value
Production	
Leontief parameter: μ	7.09
Clean productivity: A^c	1.23
Dirty productivity: A^d	1.97
Depreciation rate: δ	0.09
Preferences	
Discount factor: β	0.97
Disutility of labor: χ	118.16
Policy risk	
Probability of the carbon tax: ρ	0.10
Size of the carbon tax: τ	0.61

5.1 Climate policy risk

As discussed in Section 2, many US firms incorporate the risk of future climate policy into their long-run investment decisions. The data on internal carbon prices – and in particular, internal carbon fees – provides a tool to directly measure how firms respond to future climate policy risk. The modal carbon fee used by U.S. firms is approximately 10 dollars per ton. While this internal fee is used primarily to address climate policy risk, firms may also be motivated to use internal carbon fees to achieve warm glow or to differentiate their products as being "green". These additional motives – which simply cannot be quantified – likely inflate the carbon fee relative to the level the firms would set purely to address the climate policy risk. To address this concern, we use two approaches. First, to be conservative, we assume that half of the internal carbon fee is motivated by warm glow or "green washing" and the other half is to address climate policy risk. Consequently, we choose ρ such that it is optimal for firms to use a carbon price of 5 dollars per ton when they evaluate their investment decisions. In addition, we report a range of results corresponding to different assumptions regarding the extent to which the level of the 10 dollar per ton internal carbon fee is motivated by climate policy risk.

We take the following steps to calibrate ρ. First, we calculate the ratio of clean to dirty capital, $\hat{K}^c/\hat{K}^d$ in a deterministic steady state with a carbon tax equal to the internal carbon fee of 5 dollars per ton. We use "hat" to denote the values of macro aggregates in this deterministic steady state. Second, we calculate the value of ρ such that the ratio of clean to dirty capital, K^c/K^d in the stochastic steady state with no internal carbon tax, equals the corresponding ratio in the deterministic steady state with the carbon tax equal to the internal carbon fee: $K^c/K^d = \hat{K}^c/\hat{K}^d$. The resulting value of ρ equals 0.098. This value implies approximately a 50 percent probability that a 45 dollar per ton carbon tax will be implemented within the next eight years.

5.2 Production

We set capital's income share, α equal to one third. We choose Leontief parameter μ so that the fossil energy share of GDP equals 0.04 (Golosov et al. 2014). We normalize the fossil fuel extraction cost, ζ, to unity. We choose the depreciation rate on capital, δ, to match the investment to output ratio of 23.3 percent. We set the elasticity of substitution between clean and dirty intermediates, ε, equal to 3 (Papageorgiou et al. 2017). Following Fried (2018), we design the model so that the elasticity of substitution between the non-energy and energy intermediates, ϕ, is very close to zero. Empirically, entrepreneurs can substitute away from fossil fuel by switching to renewable energy or by increasing energy efficiency. However, both of these channels correspond to increases in the clean intermediate, instead of the non-energy intermediate . Therefore, we set the elasticity of substitution between the non-energy and energy intermediates to be very close to zero, $\phi = 0.1$.

Parameter λ determines cost firms incur from selling stranded capital. Based on the estimates in Bloom (2009), we set $\lambda = 0.43$, implying that capital looses almost half of its value when it is resold. We choose the perturbation parameter in the adjustment cost function to be very small, $\eta =$ 1e-9, to provide as close of an approximation as possible to the piecewise function in which firms only pay the adjustment cost on negative investment.

We normalize TFP in non-energy intermediate production to unity, $A^n = 1$. We choose TFP in clean, A^c, and dirty A^d, intermediate production to match the ratio of dirty capital to total capital, K^d/K and the ratio of dirty to clean intermediate production, X^d/X^c, in the US data. We construct the ratio of K^d/K from the detailed data for fixed assets and consumer durable goods. The data provides information on capital stocks dis-aggregated by type of capital (e.g. mainframes) and sector (e.g. farms). We define dirty capital as all capital that is specialized to use fossil fuel. For example, we count internal combustion engines in every sector as dirty, and we count "special industrial machinery" as dirty in sectors that directly relate to fossil energy, such as oil and gas extraction. See Appendix B for a full description of the calculation of dirty capital. Our calculated ratio of K^d/K equals 0.183.

To determine X^d/X^c, we focus on two sectors for which we directly observe clean and dirty production, electricity and transportation. Combined, electricity and transportation account for 70 percent of all US carbon emissions (EIA 2019). We define dirty electricity as any electricity that's produced from fossil fuel (e.g. coal, oil, natural gas), and clean electricity as any electricity that is produced without using fossil fuels (e.g. solar, wind, hydro, nuclear). The ratio of dirty to clean electricity generation equals, 1.67.

We define dirty and clean transportation as vehicle miles traveled in dirty and clean capital, respectively. The average vehicle contains both dirty and clean capital. Vehicles are specialized to use fossil fuel use, implying that they must contain at least some dirty capital. However, many vehicles have special capital, such as regenerative brakes, that is specifically designed to reduce fossil fuel use through improvements in fuel economy. We classify this type of capital as clean. We use data on the fuel economy of different vehicle models and the average fuel economy of the US vehicle fleet to construct the average fractions of dirty capital embodied in autos and in light-trucks (including sport utility vehicles) (see Appendix B). We find that 66 percent of autos and 80 percent of light trucks are dirty capital. Thus, we classify 66 percent of vehicle miles traveled by autos and 80 percent of vehicle miles traveled by light trucks as dirty. We classify all vehicle miles traveled by motorcycles, buses, single-unit trucks and combination trucks as dirty. The resulting ratio of dirty to clean vehicle miles traveled equals 2.63.

The ratio of dirty to clean intermediate production equals the average of the ratios of dirty to clean electricity generation and dirty to clean vehicle miles traveled, weighted by the levels of emissions in each sector.[13] The resulting weighted average yields the calibration target, $X^d/X^c = 2.17$.

5.3 Preferences

We choose the discount rate, $\beta = 0.97$, to match the US capital-output ratio of 2.6. Following Conesa et al. (2009), we set the coefficient of relative risk aversion, θ_1, equal to 2 and, consistent with Kaplan (2012), we set the Frisch elasticity, θ_2, equal to 0.5. We choose the dis-utility of hours so that workers spend one third of their total time endowment working.

[13]Combined electricity and transportation produced 3267 million metric tons of carbon dioxide in 2017; 48 percent of these emissions were from the electricity and the remaining 52 were from the transportation (EIA 2019).

6 Results

6.1 Macro-aggregates

We solve the model for three steady states: (1) a deterministic steady state in which there is no carbon tax and no risk of a future carbon tax, (2) a stochastic steady state in which there is a 9.8 percent probability of a 45 dollar per ton carbon tax, and (3) a policy steady state with a 45 dollar per ton carbon tax in place and no uncertainty about future policy. The first and second columns report the percent change in each variable from its value in the deterministic steady state in the stochastic and policy steady states, respectively. Appendix C reports the levels of each variable in the deterministic steady state.

Table 3: Effects of Climate Policy Risk on Macro-Aggregates
(Percent change from deterministic steady state)

	Stochastic SS	Policy SS
Fossil fuel: F	-1.15	-15.13
Clean to dirty capital: K^c/K^d	3.97	40.41
Clean to dirty labor: L^c/L^d	1.43	40.41
Clean to dirty intermediates: X^c/X^d	2.26	40.41
Total capital: K	-0.81	-4.09
Total labor: L	-0.02	-0.57
Output: Y	-0.32	-2.45
Consumption: C	-0.11	-1.22

Climate policy risk reduces emissions, even though there is not an actual climate policy in place. Fossil fuel consumption in the stochastic steady state is 1.15 percent lower than in the deterministic steady state. In line with the intuition from Proposition 1, this emissions reduction occurs, in part, because the risk of future policy increases the ratio of clean relative to dirty capital by 3.97 percent, pushing the economy towards cleaner production.

The reduction in emissions also occurs because climate policy risk reduces the aggregate levels of capital and labor. Following again the intuition from Proposition 1, the policy uncertainty implies that agents do not attain the allocation of capital that would be optimal ex-post, after they learn whether the government introduced the carbon tax. This misallocation reduces the return to saving and the marginal product of labor, causing households to supply less capital and fewer hours.

The distortions on capital from climate policy risk are larger than those on labor; the ratio of clean to dirty capital is 3.97 percent higher in the stochastic steady state, but the ratio of clean to dirty labor is only 1.43 percent higher. As a result, climate policy risk distorts the capital-labor ratios in the clean and dirty sectors away from the profit-maximizing levels that would prevail in a deterministic steady state. Capital responds more than labor to the policy risk because entrepreneurs must decide capital before they learn whether or not the government will introduce the carbon tax and because investment is partially irreversible, making investment decisions relatively long-lasting. Note that capital and labor respond by the same amount to the actual introduction of the carbon tax; the ratios of clean to dirty capital and clean to dirty labor both increase by 40.4 percent in the policy steady state, leaving the capital-labor ratio in each sector unchanged from its value in the deterministic steady state.

The misallocation and resulting lower levels of capital and labor reduce output and consumption in the stochastic steady state. Output is 0.3 percent lower in the stochastic steady state and consumption is 0.1 percent lower. To measure the welfare cost of the climate policy risk, we calculate the consumption-equivalent variation (CEV). The CEV equals the percent increase in consumption an agent would need in every period in the deterministic steady state so that she is indifferent between living in the deterministic or the stochastic steady state. The resulting CEV equals -0.094 percent, implying a welfare cost of the stochastic steady state equal to 0.094 percent of consumption.

6.2 Climate policy risk versus actual climate policy

The risk of future climate policy acts like an actual climate policy in the sense that it reduces emissions. To compare the effects of reducing emissions through climate policy risk instead of through an actual policy, we calculate a deterministic steady state with a carbon tax that achieves the same 1.1 percent reduction in emissions as in the stochastic steady state. The resulting tax equals 3.21 in 2017 dollars per ton. Table 4 reports the percent difference from the deterministic steady state for each variable in the stochastic steady state and in the emissions-equivalent deterministic steady state with carbon tax equal to 3.21. By construction, fossil fuel consumption decreases by 1.15 percent in both steady states; we choose the tax so that fossil fuel consumption is identical between the two steady states.

Table 4: Stochastic Steady State vs. Emissions-Equivalent Deterministic Steady State (Percent change from deterministic steady state)

	Stochastic SS	Emissions-equivalent deterministic SS
Fossil fuel: F	-1.15	-1.15
Clean to dirty capital: K^c/K^d	3.97	2.54
Clean to dirty labor: L^c/L^d	1.43	2.54
Clean to dirty intermediates: X^c/X^d	2.26	2.54
Total capital: K	-0.81	-0.32
Total labor: L	-0.02	-0.05
Output: Y	-0.32	-0.18
Consumption: C	-0.11	-0.08

While both steady states attain the same reductions in emissions, the strengths of the mechanisms that achieve this emissions reduction differ. The stochastic steady state relies more heavily on changes in the allocation of capital than labor; the ratio of clean to dirty capital increases by 3.97 percent but the ratio of clean to dirty labor only increases by 1.43 percent. In contrast, the emissions-equivalent deterministic steady state relies equally on changes in the allocations of capital and labor; the ratios of both clean to dirty capital and labor increase by 2.54 percent. Since the tax is actually in place in the emissions-equivalent steady state, it creates equal distortions to capital and labor. Additionally, the stochastic steady state relies more heavily on decreases in total capital to reduce emissions. The misallocation created by the climate policy risk results in a decrease in total capital in the stochastic steady state that is more than double the decrease in the emissions-equivalent deterministic steady state (-0.81 percent compared to -0.32 percent).

The misallocation caused by the climate policy risk implies that the cost of reducing emissions through policy risk are substantially larger than the costs from an actual policy. Indeed, output falls by -0.32 percent in the stochastic steady state, but only by -0.18 percent in the emissions-equivalent deterministic steady state. In terms of welfare, the CEV for the stochastic steady state equals -0.094, percent while the CEV for the emissions-equivalent deterministic steady state equals -0.038 percent. Thus, the welfare cost of reducing emissions through policy risk is over twice as large as the welfare costs from an actual policy.

6.3 Climate policy evaluation

The above results demonstrate that the risk of climate policy reduces emissions and has substantial effects on welfare and other macro-aggregates. Yet, most previous literature abstracts from the effects of climate policy risk when they evaluate carbon tax policy. Implicitly, these studies evaluate climate policy using the deterministic steady state as a baseline, instead of the stochastic steady state. However, if the world is more accurately represented by the stochastic steady state, then such a comparison could misrepresent the true impacts from the carbon tax.

To demonstrate the importance of the choice of the baseline for climate policy evaluation, Table 5 evaluates the long-run impacts of the 45 dollar per ton carbon tax using the two alternative baselines. The first column uses the deterministic steady state as the baseline– the exercise done by most of the existing literature. The second column uses the stochastic steady state as the baseline.

Table 5: Effect of the Baseline Steady State on Policy Evaluation

	Policy SS	
	Percent change from deterministic SS	Percent change from stochastic SS
Fossil fuel: F	-15.13	-14.15
Clean to dirty capital: K^c/K^d	40.41	35.05
Clean to dirty labor: L^c/L^d	40.41	38.43
Clean to dirty intermediates: X^c/X^d	40.41	37.30
Total capital: K	-4.09	-3.31
Total labor: L	-0.57	-0.55
Output: Y	-2.45	-2.14
Consumption: C	-1.22	-1.11

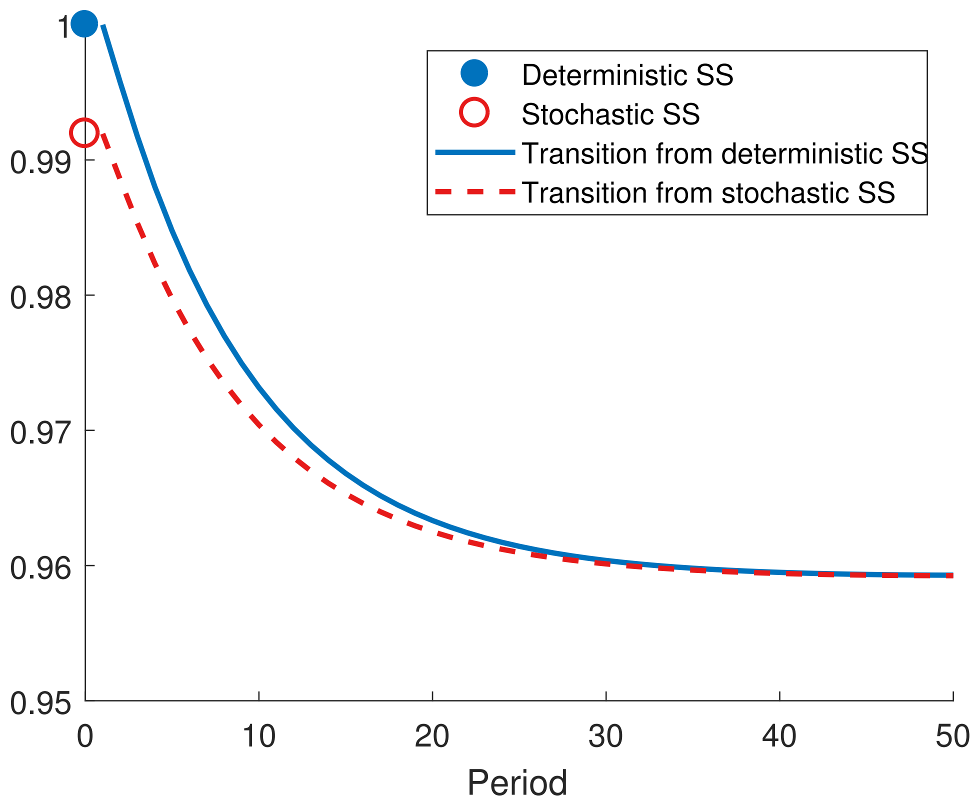
Comparing columns one and two of Table 5 reveals that failing to account for the effects of policy risk overstates both the effectiveness and cost of the carbon tax. Intuitively, since the risk of climate policy decreases emissions, some of the emissions reduction from carbon tax has already been achieved in the stochastic steady state, making the actual introduction of the policy less effective. In particular, if policymakers use the deterministic steady state as a baseline, then they would predict that the carbon tax reduces emissions by 15.13 percent. However, if the current economy is more accurately represented by the stochastic steady state, then the carbon tax only reduces emissions by 14.15 percent.

Similarly, since the climate policy risk already imposes some costs on the macroeconomy, the remaining costs from actually introducing the policy are smaller. In particular, the welfare cost of the policy steady state, measured in terms of the CEV, is 15 percent higher when the deterministic steady state is used as the baseline. The CEV of the policy steady state compared to the deterministic steady state equals -0.72 percent, while the corresponding CEV relative to the stochastic steady state is only -0.63 percent.

Even though climate policy risk implies lower long-run steady-state welfare costs of the carbon tax policy, it has almost no impact on the transitional welfare costs following the introduction of the carbon tax. The transitional CEV when the economy begins in the deterministic steady state equals -0.245 percent and when the economy in the stochastic steady state equals -0.243 percent. This near-equivalence is somewhat surprising since the climate policy risk moves the economy towards the policy steady state with the carbon tax in place. Referring to Table 3, the economy has already reduced emissions in the stochastic steady state by 1.15 percent, approximately 8 percent of the total 15.13 percent reduction in emissions implied by the policy. Similarly, the ratio of clean to dirty capital is already 3.97 percent higher in the stochastic steady state, approximately 10 percent the total 40.41 percent increase implied by the policy. As discussed in Section 6.3, these responses to climate policy risk reduce the long-run, steady state, welfare cost of climate policy.

However, any transitional welfare gains from the shift towards clean capital in the stochastic steady state are almost perfectly offset by the decline in the total capital stock. Referring to Table 3, climate policy risk reduces aggregate capital by 0.81 percent from its value in the deterministic steady state. This lower capital stock reduces agents' ability to mitigate the transitional welfare costs by decreasing investment. The solid and open circles in Figure 1 plot capital in the deterministic and stochastic steady states, respectively. We normalize capital in the deterministic steady state to unity. The solid and dashed lines plot the total capital stock over the transition from the deterministic and stochastic steady states, respectively. The higher initial levels of capital over the deterministic transition imply that agents reduce investment more when the economy starts in the deterministic steady state.

Figure 1: Total Capital Stock

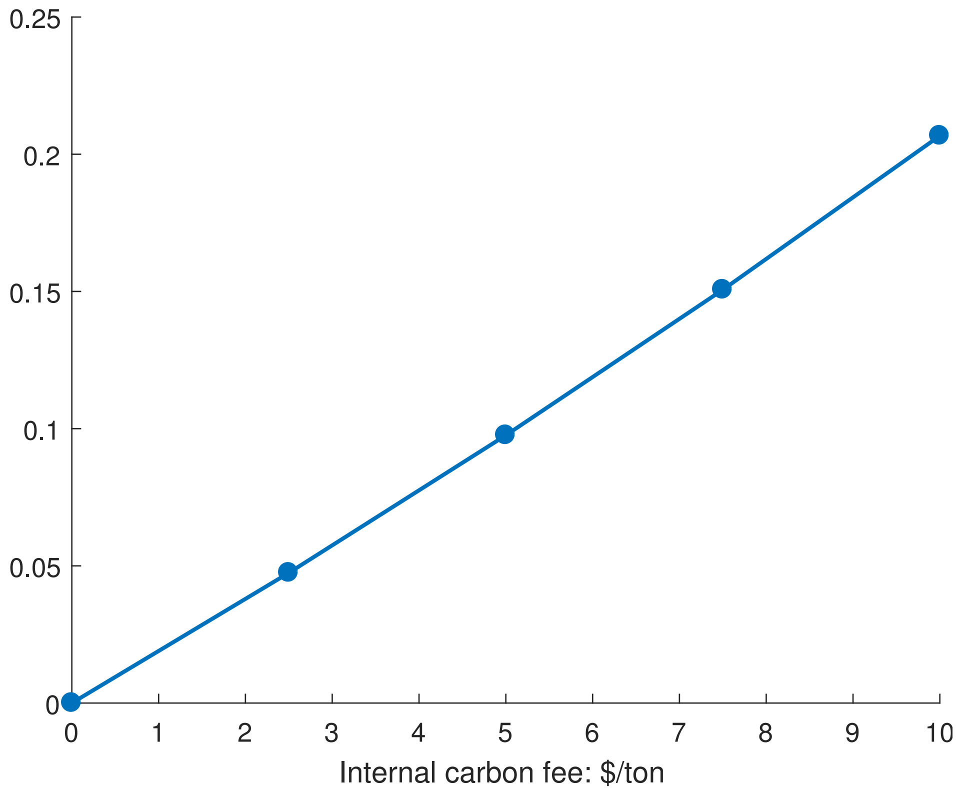


Combined, welfare consequences from changes in the capital mix and the aggregate capital stock almost perfectly offset. As a result, the risk of future climate policy in the stochastic steady state does not reduce the transitional welfare cost from actually introducing the policy.

6.4 Changes in climate policy risk

To calibrate the probability of a carbon tax in the model, we used an internal carbon price of 5 dollars per ton, approximately one half of the value we observe at US companies. This choice assumes that half of the internal carbon fee is motivated by climate policy risk and half is motivated by factors not related to climate policy risk. However, the correct split of the internal carbon fee between climate-policy-risk motives and non-climate-policy-risk motives could range from anywhere between zero and one. To understand the effects of different internal carbon fees, we recalibrate the model for internal carbon fees equal to 2.5, 7.5, and 10 dollars per ton. Figure 2 plots the corresponding probability of a carbon tax for each value of the internal carbon fee.

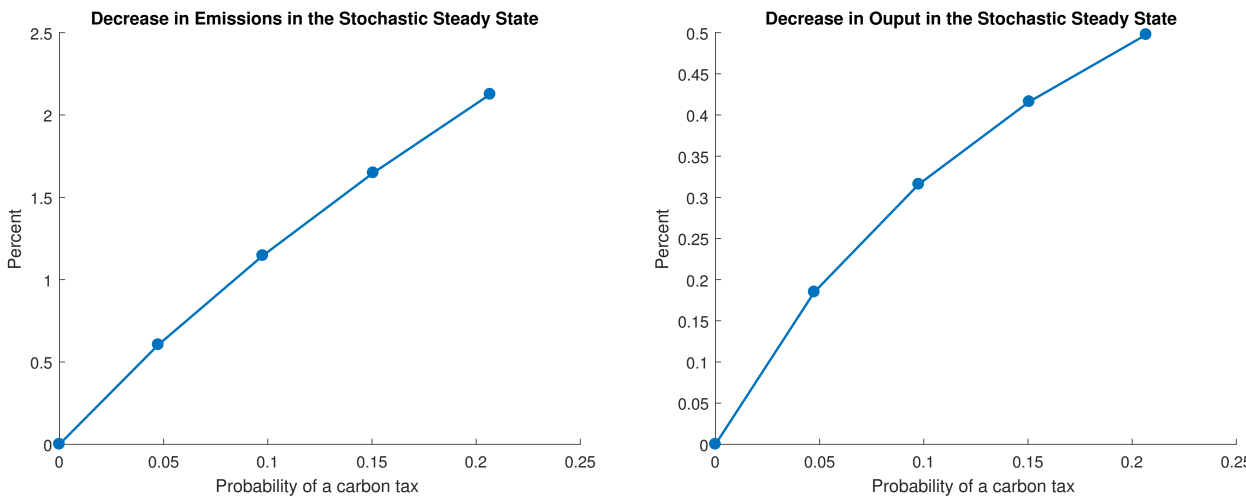
Figure 2: Probability of a Carbon Tax



The probability of the carbon tax increases linearly with the size of the internal carbon fee, ranging from approximately 5 percent when the internal fee equals 2.5 dollars per ton to 20 percent when the internal fee equals 10 dollars per ton. The 10 dollar per ton internal fee assumes that the entire fee is motivated by climate policy risk, providing an upper bound on the probability that firms place on the introduction of the 45 dollar per ton tax.

We use the alternative calibrations for different internal carbon fees to explore how changes in the probability of the carbon tax affect the macro-implications of climate policy risk. Understanding this relationship is particularly important because the probability of climate policy is likely to increase over time as climate change progresses. The left panel of Figure 3 plots the emissions reduction in the stochastic steady state for different carbon tax probabilities. All else constant, increases in the probability of the carbon tax increase the expected return to clean capital and decrease the expected return to dirty capital, resulting in larger decreases in emissions. The right panel of Figure 3 plots the reduction in output from the stochastic steady state. As with emissions, the decrease in output from the climate policy risk increases with the probability of the policy.

Figure 3: Emissions' Reduction and Welfare Cost in the Stochastic Steady State



In general, the macroeconomic response to climate policy risk grows with the likelihood of the policy. The larger macroeconomic responses imply that the errors from using the deterministic steady state, instead of the stochastic steady state, as a baseline for policy evaluation increase with the probability of climate policy. Hence, if the future is characterized by higher carbon-tax probabilities, then it will be even more important to understand and incorporate the effects of climate policy risk going forward.

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A Analytic Model

Proof of Proposition 1: The first order conditions for clean and dirty capital in the stochastic steady state equal,

$$1 = \left(\frac{1}{1+r}\right)(p^c + 1 - \delta) \tag{26}$$

$$1 = \left(\frac{1}{1+r}\right)\left[\rho(p^d - (\zeta + \tau) + 1 - \delta) + (1-\rho)(p^d - \zeta + 1 - \delta)\right] \tag{27}$$

Using the expressions for the equilibrium prices, (equation (3)), we can solve the first order conditions for the levels of clean and dirty capital in the stochastic steady state, K_0^c and K_0^d,

$$K_0^c = \left(\frac{\gamma}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}} \left(\frac{r+\delta}{r+\delta+\zeta+\rho\tau}\right)^{\frac{\theta}{1-\gamma-\theta}} \left(\frac{\theta}{\gamma}\right)^{\frac{\theta}{\gamma}} \tag{28}$$

$$K_0^d = \left(\frac{\gamma}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}} \left(\frac{r+\delta}{r+\delta+\zeta+\rho\tau}\right)^{\frac{1-\gamma}{1-\gamma-\theta}} \left(\frac{\theta}{\gamma}\right)^{\frac{1-\gamma}{\gamma}} \tag{29}$$

Observe that

$$\frac{\partial K_0^c}{\partial \rho} < 0,\ \frac{\partial K_0^c}{\partial \tau} < 0,\ \frac{\partial K_0^d}{\partial \rho} < 0,\ \frac{\partial K_0^d}{\partial \tau} < 0 \tag{30}$$

Thus, an increase in either the probability of a tax, or the expected size of the tax, reduces both the levels of clean and dirty capital in the stochastic steady state. However, the decrease in dirty capital is larger than the corresponding decrease in clean. Indeed, climate policy risk increases the ratio of clean to dirty capital,

$$\frac{K_0^c}{K_0^d} = \left(\frac{1+r+\zeta+\rho\tau-(1-\delta)(\rho(1-\lambda)+1-\rho)}{r+\delta}\right)\left(\frac{\gamma}{\theta}\right) \tag{31}$$

□

Proof of Proposition ??: We solve for the equilibrium levels of clean and dirty capital in the first period of the transition, K_1^c and K_1^d. If $K_1^c < (1-\delta)K_0^c$ or $K_1^d < (1-\delta)K_0^d$, then entrepreneurs dis-invest in capital over the transition, implying that some capital is stranded. The upper bound on the probability of the carbon tax, $\Phi(\tau)$ is the highest value of ρ, such at least one type of entrepreneur dis-invests in capital.

The first order conditions for clean and dirty capital in the first period of the transition equal:

$$1 = \left(\frac{1}{1+r}\right)(p^c + 1 - \delta) \tag{32}$$

$$1 = \left(\frac{1}{1+r}\right)(p^d - (\zeta+\tau) + 1 - \delta) \tag{33}$$

Using the expressions for the equilibrium prices, (equation (3)), we can solve the first order conditions for the level of clean and dirty capital in the first period of the transition, K_1^c and K_1^d,

$$K_1^c = \left(\frac{\gamma}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}} \left(\frac{r+\delta}{r+\delta+\zeta+\tau}\right)^{\frac{\theta}{1-\gamma-\theta}} \left(\frac{\theta}{\gamma}\right)^{\frac{\theta}{\gamma}} \tag{34}$$

$$K_1^d = \left(\frac{\gamma}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}} \left(\frac{r+\delta}{r+\delta+\zeta+\tau}\right)^{\frac{1-\gamma}{1-\gamma-\theta}} \left(\frac{\theta}{\gamma}\right)^{\frac{1-\gamma}{\gamma}} \tag{35}$$

Entrepreneurs dis-invest in capital over the transition if $K_1^d < (1-\delta)K_0^d$ or $K_1^c < (1-\delta)K_0^c$. At least one of these inequalities holds provided that

$$\rho < \Phi(\tau) \equiv \frac{(r+\delta+\zeta)\left((1-\delta)^{\frac{1-\gamma-\theta}{1-\gamma}} - 1\right)}{\tau} + (1-\delta)^{\frac{1-\gamma-\theta}{1-\gamma}} \tag{36}$$

B Calibration

Data on on US GDP, investment, and capital is from NIPA Tables 1.1, 1.1.5, and 1.5, respectively. We define capital as the sum of capital in private fixed assets and consumer durables. Similarly, we define investment as the sum of investment in private fixed assets and consumer durables. We use the average value of these ratios from 2013-2017.

Data on US electric generation by source are from Table 1_01 of the 2019 EIA Electric power monthly (www.eia.gov/electricity/data.php). Data on the vehicle miles traveled and fuel economy for the US vehicle fleet are available from Table VM-1 of the Federal Highway Administration's 2017 highway statistics.[14] Data on fuel economy by car make and model is from fueleconomy.gov. Data on total mine production by mineral type are available from Table 1 of the US Geological Survey Mineral and Commodity Summaries. Data on GDP by industry and detailed data on fixed assets and consumer durables are from the BEA.[15] We discuss the calculation of the level of dirty capital in detail below. We calculate all

[14]https://www.fhwa.dot.gov/policyinformation/statistics/2017/

[15]Fixed assets and consumer durables: apps.bea.gov/national/FA2004/Details/Index.htm. GDP by industry: apps.bea.gov/iTable/iTable.cfm?ReqID=51&step=1

energy-related moments for year 2017, the most recent year with all the available data.

We use the detailed data on fixed assets and consumer durables to construct the ratio of dirty to total capital in the US economy, K^d/K. The data provide information on the quantity of each type of capital in each sector and on the quantity of each type of durable good. The sectors are mostly correspond to the 3-digit NAICS classification, though in some cases, several 3-digit NAICS classifications are combined into a single sector. For example, the farms sector includes NAICS codes 111 and 112.

We divide the capital into three groups: group 1 corresponds to capital that is dirty or partially dirty, regardless of the sector. Group 2 corresponds to capital that is dirty or partially dirty only in sectors that are specialized to use fossil energy. Group 3 corresponds to all other types of capital. Table 6 reports the the types of capital and consumer durables that we classify as group 1 and group 2. All types not listed in Table 6 are in group 3 and correspond to either clean or non-energy capital. We do not distinguish between clean and non-energy capital in the data; we focus only on the ratio of dirty capital relative to total capital.

Table 6: Capital Classification

Group 1	Group 2
steam engines	special industrial machinery
other trucks buses	custom software
and truck trailers	own account software
internal combustion engines	chemical manufacturing except pharma and med
aircraft	other manufacturing
ships and boats	scientific research and development services
farm tractors	
construction tractors	
gas structures	
petroleum pipelines	
petroleum and natural gas structures	
other transportation equipment	
autos	
light trucks	

We classify all group 1 capital except autos and lights trucks (including sport utility vehicles) as 100 percent dirty. We view autos and light trucks as partially clean and partially dirty. Most vehicles are specialized to use fossil fuel, making them at least partially dirty. However, many vehicles also include capital that improves fuel economy, such as regenerative breaks, which is designed specifically to substitute for fossil fuel, and thus would count as clean. We use data on the fuel economy of different vehicle models and the average fuel economy of the US vehicle fleet to construct the average fractions of dirty capital embodied in autos and in light-trucks.

We define a vehicle to be 0 percent dirty if it has inverse fuel economy equal to 0 gallons/mile. At the other extreme, we define an auto or light truck to be 100 percent dirty if it has inverse fuel economy equal to the maximum in the US fleet of autos or light-trucks. We interpolate between these two extreme points to find the fraction of dirty capital embodied in the auto or light-truck with the average inverse fuel economy in the US fleet. The average inverse fuel economy of the US fleet of short-wheel-base light duty vehicles (e.g. most autos) equals 1/24.2 gallons per mile and for long-wheel-base light duty vehicles (e.g. most pick up trucks and SUVs) equals 1/17.5 gallons per mile.

To calculate the maximum inverse fuel economy among autos and light trucks in the current fleet, we use data on fuel economy by car make and model. Since fuel economy has increased over time and vehicles are long-lived, we used the fuel-economy data from model-year 2003, 15 years before 2017. We set the maximum inverse fuel economy of the current fleet equal to the 90th percentile of inverse fuel economy in model-year 2003; 1/16 gallons per mile for autos and 1/14 gallons per mile for light-trucks. Interpolating linearly between the two extremes, 0 and 100 percent dirty capital, we find that the average auto in the US fleet has 66 percent dirty capital and the average light truck has 80 percent dirty capital. In our calculation of dirty capital, we multiply the stock of autos by 0.66 and the stock of light trucks by 0.8.

We classify group 2 capital as dirty if it is in one of the following sectors which are specialized to use fossil fuel: oil and gas extraction, petroleum and coal products, plastics and rubber products, air transportation, railroad transportation, water transportation, truck transportation, pipeline transportation, other transportation and support activities. We classify group 2 capital as partially dirty if it is the mining except oil and gas extraction (NAICS code 212), or the support activities for mining (NAICS code 213) sectors. Sector 212 includes all coal and other mineral mining. To isolate the coal mining capital, we multiply all group 2 capital in this sector by 0.247, the fraction of total mine production that is from coal.

Sector 213 includes group 2 capital used to support oil and gas extraction (NAICS code 211) and coal mining, which we would classify as dirty, as well capital used to support other types of mining, which we could not classify as dirty. To isolate the dirty capital, we first calculate the fraction of mining-related value-added used for oil and gas extraction. This fraction equals the ratio of value added in sector 211 divided by the sum of value added in sectors 211 and 212, yielding a value of 0.763. Thus, 76.3 percent of group 2 capital in sector 213 corresponds to oil and gas extraction, and thus is dirty. The remaining 23.7 percent of group 2 capital in sector 213 includes support activities for coal mining (dirty) and other mining (not dirty). To isolate the coal mining capital, we multiply the remaining group 2 capital by 0.247, the fraction of total mine production that is from coal. In sum, let K_{213} denote the total group 2 capital in sector 213. We classify the following fraction of this capital as dirty: $0.763K_{213} + 0.247(1 - 0.763)K_{213}$.

C Values of Macro Aggregates in Each Steady State

Table 7: Macro Aggregates in Each Steady State

	Steady State			
	Deterministic	Stochastic	Emissions equivalent	Policy
Fossil fuel: F	0.0113	0.0112	0.0112	0.0096
Output: Y	0.2797	0.2788	0.2792	0.2729
Consumption: C	0.2030	0.2027	0.2028	0.2005
Capital: K	0.7269	0.7210	0.7246	0.6972
Labor: L	0.3331	0.3330	0.3329	0.3312
Clean Capital: K^c	0.0973	0.0987	0.0985	0.1132
Dirty Capital: K^d	0.1348	0.1316	0.1331	0.1117
Non-Energy Capital: K^n	0.4947	0.4907	0.4930	0.4722
Clean Labor: L^c	0.0446	0.0450	0.0453	0.0538
Dirty Labor: L^d	0.0618	0.0615	0.0611	0.0531
Non-Energy Labor: L^n	0.2267	0.2265	0.2265	0.2243
Clean Intermediate: X^c	0.0710	0.0717	0.0719	0.0846
Dirty Intermediate: X^d	0.1571	0.1553	0.1553	0.1334
Non-Energy Intermediate: X^n	0.2933	0.2923	0.2928	0.2868