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Climate Policy and Innovation: A Quantitative Macroeconomic Analysis†

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A carbon tax can induce innovation in green technologies. I evaluate the quantitative impact of this channel in a dynamic, general equilibrium model with endogenous innovation in fossil, green, and nonenergy inputs. I discipline the parameters using evidence from historical oil shocks, after which both energy prices and energy innovation increased substantially. I find that a carbon tax induces large changes in innovation. This innovation response increases the effectiveness of the policy at reducing emissions, resulting in a 19.2 percent decrease in the size of the carbon tax required to reduce emissions by 30 percent in 20 years. (*JEL* H23, O31, Q41, Q48, Q54, Q55, Q58)

A carbon tax can induce innovation in green technologies. Over time, these technological advances lower the cost of reducing carbon emissions. However, the magnitudes of the response of innovation and of the accompanying effects on energy prices, production, and carbon emissions remain open questions. This paper develops a general equilibrium model of endogenous innovation and energy, which I use to quantify the dynamic effects of a carbon tax. I find that the carbon tax induces large movements in innovation that have considerable effects on energy-related aggregates. Moreover, abstracting from endogenous innovation—and modeling technological progress as exogenous—results in a substantial overestimation of the size of the carbon tax necessary to attain a given reduction in emissions. A quantitative understanding of the consequences of endogenous innovation is important, since government agencies often evaluate climate mitigation projects based partly on climate-economy models that abstract from endogenous innovation.[1]

The central contribution of this paper is to quantify the interaction between endogenous innovation and climate policy in a dynamic, general equilibrium framework that explicitly models innovation in fossil energy, green energy, and nonenergy

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[1] For example, the social cost of carbon that the Environmental Protection Agency (EPA) uses to evaluate climate policies is, in part, based on climate-economy models that do not incorporate endogenous innovation.

sectors. The model builds on the macroeconomic literature on directed technical change and climate.[2] This earlier work is mainly theoretical, and the models are generally not designed for quantitative analysis.[3] For example, in many of the existing models, such as Acemoglu et al. (2012—henceforth, AABH), innovation occurs in only one energy sector (i.e., fossil or green) on the long-run balanced growth path. However, US data on fossil and green innovation show positive and substantial amounts of innovation in both of these sectors since the 1970s. To match this empirical fact, I incorporate technology spillovers across the different sectors. The spillovers imply that technology developed for one sector increases the productivity of innovation in the other sectors. One example of these spillovers between the fossil and green energy sectors is that the first mass commercialization of solar cells was driven by demand from oil companies to power the lights on their offshore rigs (Perlin 2000). If spillovers such as these are sufficiently strong, then the balanced growth path is an interior solution in which innovation occurs in both the fossil and green energy sectors.[4]

I develop a novel calibration strategy using the energy price increases triggered by oil shocks and the accompanying changes in energy production and innovation. It is important for the model to capture the empirical relationships among energy prices, production, and innovation. These are key links because many climate policies, including a carbon tax and a cap-and-trade system, create incentives to reduce fossil energy consumption through changes in energy prices. The oil shocks provide empirical evidence of the response of energy innovation and production to an aggregate increase in the energy price. This variation is particularly useful for disciplining the parameter values since economy-wide historical examples of climate policies are scarce. Thus, the calibration strategy is in itself one of the contributions of this paper.

I perform two exercises to fully explore the interactions between endogenous innovation and climate policy. First, to evaluate the dynamic effects of climate policy with endogenous innovation, I introduce a constant carbon tax into my benchmark model with endogenous innovation. Second, to quantify the importance of endogenous innovation for climate policy evaluation, I introduce a constant carbon tax into an alternative model with the endogenous innovation channel shut down. I refer to this model as the exogenous-innovation model because innovation cannot respond to the tax. In both models, I choose the size of the carbon tax to achieve a 30 percent reduction in emissions in 20 years, similar to early versions of the US emissions targets discussed in the context of the Clean Power Plan.[5]

[2] See, for example, Smulders and de Nooij (2003); Acemoglu et. al (2012); Hart (2012); Hassler, Krusell, and Olovsson (2012); Hémous (2016); Acemoglu et al. (2016). For an overview, see Fischer and Heutel (2013).

[3] For example, AABH state that their "objective is not to provide a comprehensive quantitative evaluation" (AABH, 154). One exception is Acemoglu et al. (2016), which is a quantitative paper focused on the relative roles of carbon taxes and subsidies to green energy research in the structure of optimal climate policy. A second exception is Hassler, Krusell, and Olovsson (2012), which uses US time series data to estimate an aggregate production function including capital, labor, fossil energy, and energy saving technical change.

[4] Acemoglu (2002) and Hart (2012) show that the strength of cross-sector technology spillovers can determine stability of an interior long-run balanced growth path in models of directed technical change.

[5] The primary focus of this paper is on quantifying the dynamic relationship between a carbon tax and fossil, green, and nonenergy innovation. I choose to quantify these mechanisms for a realistic climate policy and not for the optimal policy. I choose this route both because it is more realistic in the current environment and also because

There are two main findings. First, comparing the endogenous-innovation model with and without the tax, I find that the tax induces considerable movements in innovation, energy prices, and other macroeconomic aggregates. For example, after 20 years, the tax causes green innovation to be 50 percent higher and fossil innovation to be 60 percent lower than what they would have been without the tax. These movements in innovation are accompanied by substantial changes in relative prices. In the model with the tax, the relative price of green compared to fossil energy is 7 percent lower in 20 years and 17 percent lower on the new balanced growth path than in the model without the tax.

Second, comparing the results from the tax in the exogenous- and endogenous-innovation models, I find that endogenous innovation has substantial implications for the effectiveness of the carbon tax and for the relative price of green energy. The carbon taxes required to achieve the emissions target in the exogenous- and endogenous-innovation models are 30.3 and 24.5 in 2013 dollars per ton of CO_2, respectively. Endogenous innovation reduces the carbon tax by 19.2 percent because it increases incentives for carbon abatement. The intuition for this result is that regardless of whether innovation is endogenous, the carbon tax operates through prices to shift demand from fossil to green energy, reducing emissions. However, when innovation is endogenous, this shift in demand spurs green innovation. Over time, the increase in green innovation reduces the marginal cost of producing green energy, lowering its equilibrium price and creating stronger incentives for agents to switch from fossil to green. Thus, endogenous innovation amplifies the price incentives created by the carbon tax, implying that the emissions target can be achieved with a 19.2 percent smaller tax.

Additionally, I find that endogenous innovation has offsetting effects on the gross welfare costs of attaining a given emissions target.[6] The carbon tax is smaller when innovation is endogenous, and, hence, the accompanying gross distortionary cost is smaller. However, the shift in innovation from fossil to green energy in response to the tax reduces the aggregate growth rate along the transition path to a new long-run equilibrium, raising the gross welfare cost of the policy. As a result, the overall effect of endogenous innovation on the gross welfare costs of the carbon tax is small. In particular, the consumption equivalent variation (CEV) of the tax is -0.3 percent in the endogenous-innovation model and -0.4 percent in the exogenous-innovation model.

In addition to the literature on directed technical change and climate, this paper builds on an environmental literature on the effects of endogenous innovation in integrated assessment climate-economy models.[7] Unlike much of this previous environmental literature, the present paper specifically models the general equilibrium

calculating optimal policy requires additional assumptions, which can make the underlying mechanisms governing the relationship between endogenous innovation and climate policy less transparent. For example, a rigorous calculation of the optimal policy requires a damage function, a realistic depiction of the carbon cycle, a plausible time frame for the analysis, a reasonable rate of time preference, and assumptions about carbon emissions from other, non-modeled, countries.

[6] The carbon tax is designed to correct the externality from carbon emissions. Therefore, relative to the social optimum, the carbon tax should not generate first-order distortionary or welfare costs. Here, I use the term "gross" to denote changes relative to the baseline outcome, which does not include the damage from climate change.

[7] See, for example, Grubb, Duong, and Chapuis (1994); Goulder and Schneider (1999); Nordhaus (2002); van der Zwaan et al. (2002); Popp (2004); Gerlagh (2008); and Popp, Newell, and Jaffe (2009), which provides a nice overview.

effects from endogenous innovation in each of two energy sectors (fossil and green) and in a third sector comprising the rest of the economy. These features influence the effects of endogenous innovation on climate policy outcomes along three important dimensions. First, the potential for innovation in fossil, green, and nonenergy sectors is important for obtaining a plausible calibration that applies to the whole economy. Second, the general equilibrium, three-sector framework fully endogenizes the relative price of green to fossil energy. And third, the three sectors imply that increased green innovation can crowd out fossil innovation and/or nonenergy innovation. Additionally, this paper also relates to the growing macroeconomic literature on energy and climate with exogenous innovation.[8]

The paper proceeds as follows. Sections I and II describe the model. Section III discusses the oil shocks and the calibration strategy. Section IV presents the main results, sensitivity analysis, and comparison with earlier work. Section V concludes.

I. Model

I adapt the standard directed technical change framework (Acemoglu 2002) to a setting with fossil, green, and nonenergy intermediate inputs and oil shocks. Fossil energy refers to energy derived from coal, oil, or natural gas. Green energy refers to energy derived from any non-carbon energy source. This category includes renewable energy, such as wind and solar, as well as nuclear energy and energy savings from improved fossil energy efficiency, such as better insulation, higher fuel economy, etc.

A. *Final Good*

The unique final consumption good, Y, is produced competitively from energy, E, and nonenergy inputs, N, according to the CES production function

$$Y_t = \left(\delta_y E_t^{\frac{\varepsilon_y - 1}{\varepsilon_y}} + (1-\delta_y) N_t^{\frac{\varepsilon_y - 1}{\varepsilon_y}}\right)^{\frac{\varepsilon_y}{\varepsilon_y - 1}}, \tag{1}$$

where $\varepsilon_y < 1$ is the elasticity of substitution between the energy and nonenergy inputs. Energy is a nested CES composite of fossil energy, green energy, and oil imports,

$$E_t = \left(\tilde{F}_t^{\frac{\varepsilon_e - 1}{\varepsilon_e}} + G_t^{\frac{\varepsilon_e - 1}{\varepsilon_e}}\right)^{\frac{\varepsilon_e}{\varepsilon_e - 1}}, \tag{2}$$

where

$$\tilde{F}_t = \left(\delta_{\tilde{F}} F_t^{\frac{\varepsilon_f - 1}{\varepsilon_f}} + (1-\delta_{\tilde{F}})(O_t^*)^{\frac{\varepsilon_f - 1}{\varepsilon_f}}\right)^{\frac{\varepsilon_f}{\varepsilon_f - 1}}.$$

[8] See, for example, Nordhaus (2008), Krusell and Smith (2009), Hassler and Krusell (2012), and Golosov et al. (2014).

Parameter $1 < \varepsilon_f < \infty$ denotes the elasticity of substitution between fossil energy (produced domestically), F, and oil imports, O^*. Since fossil energy is a mixture of coal, oil, and natural gas, oil imports and fossil energy are not perfect substitutes. Parameter $\varepsilon_e > 1$ is the elasticity of substitution between green energy, G, and the CES composite comprised of fossil energy and oil imports, $\tilde{F}$.[9] The final good is the numeraire.

B. *Fossil, Green, and Nonenergy Intermediate Inputs*

Fossil, green, and nonenergy intermediate inputs are produced competitively and sold at market prices to the final good producer.[10] The production functions for each intermediate $j \in \{f, g, n\}$ are constant returns to scale in labor, L_j, and a unit mass of sector-specific machines, each indexed by i, X_{ji},

$$(3) \qquad F_t = L_{ft}^{1-\alpha_f} \int_0^1 X_{fit}^{\alpha_f} A_{fit}^{1-\alpha_f}\, di, \quad G_t = L_{gt}^{1-\alpha_g} \int_0^1 X_{git}^{\alpha_g} A_{git}^{1-\alpha_g}\, di$$

$$N_t = L_{nt}^{1-\alpha_n} \int_0^1 X_{nit}^{\alpha_n} A_{nit}^{1-\alpha_n}\, di.$$

Variable A_{ji} denotes the technology embodied in machine X_{ji}, and α_j is the factor share of machines in sector j. A representative intermediate-goods producer chooses machines and labor to maximize profits, taking prices as given. Labor market clearing requires that $L_{ft} + L_{gt} + L_{nt} \leq L$, where L is the fixed exogenous supply of workers in the economy.

C. *Machines*

There is a unit mass of machine producers in each of the three sectors. The machine producers sell their machines to the intermediate-goods producers in their specific sectors. Each machine embodies technology. A machine producer can hire scientists to innovate on the embodied technology. A machine costs one unit of the final good to produce, regardless of the sector or the level of technology embodied in the machine. The market for scientists is competitive, and the machine producer must pay the scientists he hires the market wage, w_{sj}. However, the market for

[9] Following AABH and Hémous (2016), I do not include a distribution parameter between green energy, G, and the CES composite comprised of fossil energy and oil imports, $\tilde{F}$. Differences in the quantities of $\tilde{F}$ and G result exclusively from differences in their relative prices and not from an underlying asymmetry in the production function. Both $\tilde{F}$ and G contribute equally at the margin to the energy composite, E, when relative prices are the same. For example, a boiler that uses one less ton of coal (higher G) is equivalent to additional coal (higher $\tilde{F}$). However, the finite elasticity of substitution implies that there is some heterogeneity in the production process, so agents do not substitute indefinitely into either $\tilde{F}$ or G.

[10] This model of fossil energy production abstracts from resource scarcity. While the supplies of fossil energy are finite, historically, fossil energy prices have not followed the predictions from the standard Hotelling model of an exhaustible resource (Hamilton 2009). Moreover, given the presence of climate change, scarcity constraints on fossil energy extraction are less likely to bind. For example, the International Energy Agency estimates that if the world is to remain below the two degree target, then no more than one-third of the proven reserves of fossil energy can be consumed prior to 2050 (International Energy Agency 2012).

machines is monopolistically competitive, and the machine producers earn positive profits from the sale of their machines.

The evolution of technology for machine producer i in each sector j is

$$(4) \qquad A_{fit} = A_{ft-1}\left(1+\gamma\left(\frac{S_{fit}}{\rho_f}\right)^{\eta}\left(\frac{A_{t-1}}{A_{ft-1}}\right)^{\phi}\right),$$

$$A_{git} = A_{gt-1}\left(1+\gamma\left(\frac{S_{git}}{\rho_g}\right)^{\eta}\left(\frac{A_{t-1}}{A_{gt-1}}\right)^{\phi}\right),$$

$$A_{nit} = A_{nt-1}\left(1+\gamma\left(\frac{S_{nit}}{\rho_n}\right)^{\eta}\left(\frac{A_{t-1}}{A_{nt-1}}\right)^{\phi}\right),$$

where S_{ji} denotes the number of scientists who work for machine producer i in sector j. Scientists affect the growth rate of the machine producer's technology. Hence, there is path dependence in innovation; higher existing technology in a sector increases the marginal product of research in that sector.[11]

Parameter $\eta \in (0,1)$ implies that there are diminishing returns to scientific research within a given period. This modeling choice captures the "stepping on toes" effect discussed in the endogenous growth literature, where scientists are more likely to duplicate discoveries within a given period (Jones and Williams 1998). Parameter γ measures the efficiency with which scientists produce new ideas.

Parameters ρ_f, ρ_g, and ρ_n adjust for differences in sector diversity. Specifically, ρ_f is the number of processes on which a scientist can innovate in fossil energy. Fossil energy scientists divide their time equally among all available processes (and likewise for green and nonenergy scientists). Accounting for differences in sector diversity is particularly important because there are diminishing returns to innovation in each sector. Without a diversity adjustment, the marginal product of a nonenergy scientist is much lower than that of an energy scientist simply because there are more nonenergy scientists.

Variable A_j, denotes the aggregate (average) level of technology in sector j:

$$(5) \qquad A_{ft} = \int_0^1 A_{fit}\, di, \quad A_{gt} = \int_0^1 A_{git}\, di, \quad A_{nt} = \int_0^1 A_{nit}\, di.$$

I define aggregate technology, A, as the average of the technologies in each sector weighted by the number of processes:

$$(6) \qquad A_t = \frac{\rho_f A_{ft} + \rho_g A_{gt} + \rho_n A_{nt}}{\rho_f + \rho_g + \rho_n}.$$

The TFP catchup ratios, $\left(A_{t-1}/A_{jt-1}\right)^{\phi}$, incorporate technology spillovers across the different sectors. The intuition for these cross-sector spillovers is that if sector j

[11] The main differences between the specification in equation (4) and the specification used in AABH are the TFP catch-up term $\left(A_{t-1}/A_{jt-1}\right)^{\phi}$ and the diminishing returns to innovation, η.

is relatively backward, then there are many ideas from other sectors that have not yet been applied in sector j. This "low-hanging fruit" increases the productivity of research in sector j. Parameter $\phi \in (0,1)$ determines the strength of the cross-sector spillovers.

In addition to the cross-sector technology spillovers, the technology accumulation process also incorporates technology spillovers within a sector after one period. The technology of machine producer i in sector j tomorrow depends on the level of knowledge in sector j today and on any new ideas that machine producer i accumulates from hiring scientists. Hence, a given machine producer's discoveries are secret for one period. After the period is over, other machine producers in his sector observe his discoveries and can incorporate them into their own innovation processes. This modeling choice is empirically reasonable, provided that the period is sufficiently long and is in line with similar assumptions made in the literature (e.g., AABH; Hémous 2016). I discuss evidence of these within-sector spillovers in fossil and green energy and an appropriate period length in online Appendix B.

Each machine producer chooses the quantity of machines, the machine price, and the number of scientists, to maximize his profits. He takes the existing levels of technology as given. Scientist market clearing requires that $S_{ft} + S_{gt} + S_{nt} \leq S$, where S is the fixed exogenous supply of scientists in the economy and S_j is the number of scientists in sector j.

D. *An Oil Shock and a Carbon Tax*

Carbon emissions, $\mathcal{E}$, accumulate from the use of fossil energy and oil imports,

$$\mathcal{E}_t = \omega_f F_t + \omega_o O_t^*.$$

Parameters ω_f and ω_o convert fossil energy and oil imports into carbon emissions.

The supply of oil imports is perfectly elastic at exogenous price, P_o^*. An oil shock is an exogenous increase in P_o^*. I choose to model the price of oil imports as exogenous because this is a simple way to model the oil shocks, which I use for calibration. All other prices are endogenous and respond to the oil price shock through the model's general equilibrium channels. In particular, the oil price shock increases fossil energy demand, raising the equilibrium price of domestic fossil energy, consistent with the empirical observations of oil shocks and domestic fossil energy prices.

A carbon tax places a price on carbon emissions. Thus, the tax, τ, is a tax per unit of carbon consumed, which is independent of the price. The tax increases the price of fossil energy from P_{ft} to $P_{ft} + \tau_f$ and the price of oil imports from P_{ot}^* to $P_{ot}^* + \tau_o$, where $\tau_f = \tau \times$ (carbon content of fossil energy) and $\tau_o = \tau \times$ (carbon content of oil imports).

E. *Household*

The representative household is inhabited by a unit mass of machine producers in each sector, L workers, and S scientists. The relative supplies of workers and scientists are fixed. Additionally, I assume that both workers and scientists are mobile across sectors so that they can switch sectors without incurring adjustment costs. Zero adjustment costs are reasonable provided the time period is sufficiently long. Such an assumption can be further justified with a broad view of scientists and workers. For example, the skills of a chemist (scientist) and a construction worker (worker) are needed in all three sectors, suggesting that these types of scientists and workers would not incur substantial adjustment costs from switching sectors in the long run.

The utility function is $U(C_t) = C_t^{1-\theta}/(1-\theta)$, where variable C denotes household consumption and parameter $1/\theta$ is the intertemporal elasticity of substitution. There is no mechanism through which the household can save, and, thus, it consumes its income.[12] The budget constraint is

$$C_t = w_{lft}L_{ft} + w_{lgt}L_{gt} + w_{lnt}L_{nt} + w_{sft}S_{ft} + w_{sgt}S_{gt} + w_{snt}S_{nt} + \int_0^1 (\pi_{fit} + \pi_{git} + \pi_{nit})\, di + T_t. \tag{7}$$

Variable π_{ji} denotes profits to machine producer i in sector j, and variable T denotes lump sum transfers from the carbon tax.

The aggregate resource constraint implies that the final good can be consumed, converted to machines, or used to purchase oil imports:

$$Y_t = C_t + \int_0^1 (X_{fit} + X_{git} + X_{nit})\, di + P_{ot}^* O_t^*. \tag{8}$$

F. *Equilibrium*

A *decentralized equilibrium* consists of sequences of wages $(w_{lft}, w_{lgt}, w_{lnt}, w_{sft}, w_{sgt}, w_{snt})$, prices for machines $(P_{fit}^x, P_{git}^x, P_{nit}^x)$, prices for intermediates (P_{ft}, P_{gt}, P_{nt}), demands for machines $(X_{fit}^d, X_{git}^d, X_{nit}^d)$, demands for intermediates (F_t^d, G_t^d, N_t^d), demands for labor $(L_{ft}^d, L_{gt}^d, L_{nt}^d)$, demands for scientists $(S_{ft}^d, S_{gt}^d, S_{nt}^d)$, supplies of machines $(X_{fit}^s, X_{git}^s, X_{nit}^s)$, supplies of intermediates, (F_t^s, G_t^s, N_t^s), supplies of labor $(L_{ft}^s, L_{gt}^s, L_{nt}^s)$, and supplies of scientists $(S_{ft}^s, S_{gt}^s, S_{nt}^s)$ such that given a sequence of oil import prices (P_{ot}^*):

(i) Agents optimize: $(P_{fit}^x, P_{git}^x, P_{nit}^x)$, $(S_{ft}^d, S_{gt}^d, S_{nt}^d)$, and $(X_{fit}^s, X_{git}^s, X_{nit}^s)$ maximize the machine producers' profits; $(X_{fit}^d, X_{git}^d, X_{nit}^d)$ and $(L_{ft}^d, L_{gt}^d, L_{nt}^d)$ maximize the intermediate-goods producers' profits; $(F_t^d, G_t^d, N_t^d, (O_t^*)^d)$ maximize the final-good producer's profits; $(L_{ft}^s, L_{gt}^s, L_{nt}^s)$ and $(S_{ft}^s, S_{gt}^s, S_{nt}^s)$ maximize the household's utility.

[12] This is a standard simplification in the directed technical literature (e.g., Acemoglu 2002; AABH), which considerably simplifies the solution.

(ii) Markets clear: $(P^x_{fit}, P^x_{git}, P^x_{nit})$ clear the machine producer markets; (P_{ft}, P_{gt}, P_{nt}) clear the intermediate input markets; $(w_{lft}, w_{lgt}, w_{lnt})$ and $(w_{sft}, w_{sgt}, w_{snt})$ clear the labor and scientist markets, respectively.

II. Discussion

The model is designed to endogenize the innovation response to energy price increases triggered by carbon taxes and oil shocks. Both oil shocks and carbon taxes enter the model through the final-good producer's demand for energy inputs. The optimization problem of the representative final-good producer is

$$\max_{F_t, G_t, N_t, O_t^*} \left\{ Y_t - (P_{ft} + \tau_f) F_t - P_{gt} G_t - (P^*_{ot} + \tau_o) O^*_t - P_{nt} N_t \right\}, \tag{9}$$

subject to the production technology defined in equations (1) and (2). The direct effect of the carbon tax is to increase both the fossil energy and the oil import prices, while the direct effect of the oil shock is to increase only the oil import price.

The first-order conditions for the machine producer imply that the wages to scientists in each sector are given by (see online Appendix A for the full derivation):

$$\begin{aligned} w_{sft} &= \frac{\eta\gamma\alpha_f A_{ft-1}\left(\frac{S_{ft}}{\rho_f}\right)^{\eta}\left(\frac{A_{t-1}}{A_{ft-1}}\right)^{\phi} P_{ft}F_t}{\left(\frac{1}{1-\alpha_f}\right)S_{ft}A_{ft}}, \\ w_{sgt} &= \frac{\eta\gamma\alpha_g A_{gt-1}\left(\frac{S_{gt}}{\rho_g}\right)^{\eta}\left(\frac{A_{t-1}}{A_{gt-1}}\right)^{\phi} P_{gt}G_t}{\left(\frac{1}{1-\alpha_g}\right)S_{gt}A_{gt}}, \\ w_{snt} &= \frac{\eta\gamma\alpha_n A_{nt-1}\left(\frac{S_{nt}}{\rho_n}\right)^{\eta}\left(\frac{A_{t-1}}{A_{nt-1}}\right)^{\phi} P_{nt}N_t}{\left(\frac{1}{1-\alpha_n}\right)S_{nt}A_{nt}}. \end{aligned} \tag{10}$$

Since the market for scientists is perfectly competitive, the wage of a scientist in a given sector equals the marginal return to innovation in that sector. Thus, equation (10) shows that the marginal return to fossil innovation is increasing in the value of fossil energy production, $P_f F$. This relationship implies that the product of price and quantity, $P_f F$, as opposed to each individual component, (P_f and F) is what matters for innovation incentives. Thus, it is important for the quantitative analysis that the calibrated model match this product of price times quantity. Similarly, the marginal return to green innovation is increasing in the value of green energy production, $P_g G$.

Oil shocks and carbon taxes have opposite effects on fossil energy innovation incentives. An oil shock increases fossil energy demand, raising the equilibrium value of $P_f F$ and the accompanying innovation incentives. A carbon tax decreases fossil energy demand, reducing the equilibrium value of $P_f F$, and the accompanying innovation incentives. In contrast to their opposite effects on fossil innovation, both oil shocks and carbon taxes increase green innovation incentives. Each of these shocks increases demand for green energy, raising the equilibrium value of $P_g G$ and the accompanying innovation incentives.

The technology accumulation process incorporates both path dependence and cross-sector technology spillovers. These two drivers of innovation are captured in the marginal return by the term, A_{ft-1} and the catchup ratio, $\left(A_{t-1}/A_{ft-1}\right)^{\phi}$. All else constant, path dependence implies that the marginal return to innovation is higher in the more advanced sectors, while the catchup effect implies that the marginal return to innovation is higher in the less advanced sectors.

Parameter ϕ measures the strength of the productivity catchup effect. If $\phi = 0$, there are no cross-sector spillovers and there is full path dependence, as in AABH and Hémous (2016). Since fossil and green energy are gross substitutes ($\varepsilon_e > 1$), this strong path dependence implies that innovation in one energy sector raises the relative marginal product of innovation in that sector by so much that the only stable balanced growth paths are corner solutions in which innovation occurs in only one form of energy.[13] In contrast, if $\phi = 1$, the marginal return to innovation in a sector is independent of the previous level of technology in that sector, and, hence, there is no path dependence. In this case, there exists a stable interior balanced growth path in which innovation occurs in both forms of energy. The value of ϕ determines the relative strengths of the path dependence and cross-sector spillovers and, thus, governs the stability of the interior balanced growth path.[14]

III. Calibration

I discuss the choice of the model time period, the data for the calibration, and, finally, the calibration of the model parameters. Following standard procedure (e.g., Gourinchas and Parker 2002), I calibrate the production and innovation components of the model in two steps. In the first step, I calibrate a group of parameters directly from the data series. In the second step, I use historical oil shocks and the accompanying data on energy production and innovation to jointly calibrate the remaining parameters. A growing empirical literature that finds a causal relationship between a change in energy prices and energy innovation supports this approach.[15]

A. *Time Period*

The time period in the model is five years. This choice implies that technology spillovers within a sector occur in five years. To determine this time period, I examine the rate of technology spillovers experienced in solar power (a green industry)

[13] Innovation will also occur in the nonenergy sector since the nonenergy and energy sectors are gross complements. The diminishing returns to innovation imply that the corner solution balanced growth paths only exist asymptotically.

[14] Acemoglu (2002) and Hart (2012) show that the strength of the cross-sector technology spillovers can determine stability of an interior long-run balanced growth path in models of directed technical change.

[15] See, for example, Newell, Jaffe, and Stavins (1999); Popp (2002); Crabb and Johnson (2007); Lanzi and Sue Wing (2010); Hassler, Krusell, and Olovsson (2012); Aghion et al. (2016).

and in offshore drilling (a fossil industry). In both cases, within-sector technology spillovers frequently occur in less than five years. For a full discussion of the spillovers in these two industries, see online Appendix B.

B. *Data*

The National Science Foundation's (NSF) Survey of Industrial Research and Development reports innovation expenditures by US companies from 1953–2007. The data include both company- and government-funded R&D expenditures.[16,17] From 1972–2007, the survey reports energy specific R&D expenditures. I split the R&D expenditures into fossil, green, and nonenergy categories.[18] Fossil innovation corresponds to any R&D expenditures on coal, oil, or natural gas. Green innovation corresponds to any energy R&D expenditures that are not in coal, oil, or natural gas. This category includes renewables and nuclear, as well as energy conservation and efficiency.[19] This mapping reflects the broad definition of green energy to encompass both non-carbon sources of energy and improvements in conservation and efficiency, as discussed in Section I. Finally, I measure nonenergy R&D expenditures as the difference between total and energy R&D expenditures.

Data on fossil energy prices, fossil energy production, and oil import prices and quantities are from the US Energy Information Administration. Data on labor, fixed assets, output, and employee compensation are from the US Bureau of Economic Analysis (BEA) industry accounts. Following Mork (1989), I use the refiner acquisition cost of imported crude oil to measure the price of oil imports. This measure captures differences in the foreign and domestic prices of crude oil due to price controls and other policies.

C. *Direct Calibration*

Table 1 reports the parameter values. I calibrate the following six parameters directly from the data series: $\{\alpha_f, \alpha_n, \rho_f, \rho_g, S, \omega\}$, where $\omega = \omega_o/\omega_f$ measures the carbon content of oil imports relative to that of domestic fossil energy.

[16] Government-funded research expenditures are defined as "the cost of R&D performed within the company under federal R&D contracts or subcontracts, and R&D portions of federal procurement contracts and subcontracts." The NSF data and documentation are available for download at: https://www.nsf.gov/statistics/iris/start.cfm.

[17] I include both government- and company-funded research expenditures because government-funded R&D in the early 1970s arguably responded to market-based incentives. Prior to President Ronald Reagan taking office in 1981, a specific goal of federal energy policy was to accelerate the development of new marketable technologies, making federally funded R&D a potential substitute for company funded R&D (see Popp 2002 for further discussion). Additionally, Lichtenberg (1987) finds a substantial response of government funded R&D to changes in the relative price of energy.

[18] The 1972 data only include energy and nonenergy R&D; the split between fossil and green is not available during this year. The data after 1972 does include the split between fossil and green. Therefore, I assume that the relative split between fossil and green in 1972 is the same as it is in 1973.

[19] Conceptually, it is important to include nuclear energy R&D as part of green R&D because this was seen as the main viable alternative to fossil energy in the early 1970s. Major disasters such as the meltdowns at Chernobyl and Three-Mile Island had not yet occurred. Excluding nuclear energy would therefore understate the innovation in nonfossil energy. Specifically, if agents did not see nuclear as a viable alternative to fossil energy, then there would have presumably been more investment in other green energy forms of R&D. However, quantitatively, recalibrating and resolving the model excluding nuclear R&D does not make a substantial difference in the effects of endogenous innovation on the size of the carbon tax required to achieve the emissions target.

TABLE 1—PARAMETER VALUES

Parameter	Model value	Source
Final good production		
Output elasticity of substitution: ε_y	0.05	—
Energy elasticity of substitution: ε_e	1.50	—
Fossil elasticity of substitution: ε_f	6.24	Method of moments
Distribution parameter:† δ_y	1.44e-38	Method of moments
Distribution parameter: $\delta_{\tilde{F}}$	0.47	Method of moments
Intermediates production		
Labor share in fossil energy: $1-\alpha_f$	0.28	Data
Labor share in green energy: $1-\alpha_g$	0.09	Method of moments
Labor share in nonenergy: $1-\alpha_n$	0.64	Data
Number of workers: L	1	Normalization
1971–1975 productivity shock: ν	0.64	Method of moments
Research		
Cross-sector spillovers: ϕ	0.50	—
Diminishing returns: η	0.79	Method of moments
Scientist efficiency: γ	3.96	Method of moments
Sector size: ρ_f	0.01	Data
Sector size: ρ_g	0.01	Data
Sector size: ρ_n	1	Normalization
Number of scientists: S	0.01	Data
Climate		
Emissions conversion: ω	1.03	Data

† The value of the economically relevant quantity is $\left(\delta_y/(1-\delta_y)\right)^{\varepsilon_y} = 0.01$.

I calibrate the labor share in fossil energy, $1-\alpha_f$, as the cost share of labor in value added in the fossil energy sector. Fossil energy corresponds to coal, oil, and natural gas extraction, as well as to the production of petroleum and coal products (such as gasoline). I map fossil energy to the mining and the petroleum and coal products industries (NAICS codes 21 and 324) in the BEA accounts. The average labor share over the past 25 years (1987–2012) in these two industries combined is 0.28. I use the standard value for labor share in GDP, 0.64, for nonenergy labor share, $1-\alpha_n$, since the nonenergy sector comprises most of the economy.

I normalize the workforce to unity, $L = 1$. Approximately 1 percent of workers are engaged in R&D in the United States (Jones and Vollrath 2013), and, so I set the number of scientists $S = 0.01$. I also normalize ρ_n to unity. Thus, parameters ρ_f and ρ_g capture the number of processes in the fossil and green energy sectors relative to the number of processes in the nonenergy sector. I measure these relative levels of diversity by the long-run average fractions of fossil R&D to nonenergy R&D and green R&D to nonenergy R&D. This measure assumes that average R&D is equal across all processes in the long run.

Additionally, I design the model so that the elasticity of substitution between energy and nonenergy in the production of output, ε_y, is close to zero. As this elasticity reaches zero, the specification becomes Leontief. The Leontief condition implies that nonenergy inputs, N, and the CES composite comprised of the energy inputs, E, are required in fixed proportions to produce output. Even with this Leontief condition, the amount of the composite comprised of oil imports and fossil energy, $\tilde{F}$, used to produce a unit of output can vary since agents can substitute green energy for $\tilde{F}$. Empirically, this substitution occurs through increases in renewable energy, nuclear, and/or energy efficiency. As discussed in Section I, green energy includes all of these channels. Thus, any reduction in $\tilde{F}$ requires an increase in green energy to produce the same quantity of output. Note that when the elasticity of substitution is exactly zero, there are kinks in the equilibrium conditions that are difficult to handle numerically. To avoid these numerical difficulties, I set the elasticity of substitution slightly greater than zero, $\varepsilon_y = 0.05$.

I use a conservative value for the elasticity of substitution between green energy and the composite comprised of fossil energy and oil imports, $\varepsilon_e = 1.5$. This parameter is particularly difficult to pin down because of the lack of aggregate data on green energy prices and quantities. Values of similar parameters used in integrated assessment and macroeconomic models typically range from unity to ten (Lanzi and Sue Wing 2010; AABH) while empirical estimates from Lanzi and Sue Wing (2010) and Papageorgiou, Saam, and Schulte (2013) range from 1.6–3. Section IVD considers robustness analysis for different values of ε_e.

Finally, I calibrate ω, the ratio of the carbon content of oil to the carbon content of fossil energy. I measure the carbon content of fossil energy as the weighted average of the carbon content of coal, oil, and natural gas, where the weights are determined by the average quantities produced in the United States in 2012.

D. *A Method of Moments*

I jointly calibrate the remaining parameters $\{\alpha_g, \varepsilon_f, \delta_{\tilde{F}}, \delta_y, \eta, \gamma\}$ to capture the relationships between energy prices, production, and innovation. To obtain empirical evidence of these relationships, I analyze the energy price increases triggered by historical oil shocks and the accompanying changes in energy production and innovation. Empirically, these oil shocks led to large increases in the prices of substitute fossil fuels (such as coal and natural gas) in addition to the increases in the price of oil. Thus, like a carbon tax, the oil shocks created a substantial increase in the price of domestic fossil energy.

In an ideal setting, to calibrate the model parameters I would use data on energy price increases triggered by climate policy instead of by oil shocks. However, there are not many economy-wide historical examples of climate policies. The closest example is the Emissions Trading System in the European Union (EU-ETS). However the EU-ETS carbon permit price has been very unstable. In both the pilot period (2005–2007) and the first trading period (2008–2012), the EU over-allocated carbon permits and the price effectively fell to zero. Another alternative to using oil shocks is to use the variation in gas taxes (or other energy taxes) across countries. However, these taxes are usually specific to a single sector, such as transportation, and, thus, are not necessarily representative of how the aggregate economy would respond to a carbon tax that applies to all carbon-emitting fuels. The oil shocks and the accompanying data on energy production and innovation are a rare historical example of the economic response to an aggregate increase in fossil energy prices.

I focus on the oil shocks triggered by the rise of the Organization of Petroleum Exporting Countries (OPEC) in the first half of the 1970s. I use the oil shocks of the early 1970s instead of more recent oil shocks for two reasons. First, because a carbon tax will likely be permanent, it is important to calibrate to an aggregate increase in energy prices that agents at least believe to be permanent. After the rise of OPEC in the early 1970s, there was a sense that the economy had permanently switched from a low-energy-price regime to a high-energy-price regime. Energy price forecasts during the 1970s and early 1980s generally do not predict falling energy prices, suggesting that agents believed that the oil shocks were very long-lived.[20] However, after oil prices began to fall in the mid-1980s, agents potentially learned that this regime switch was not permanent and that oil shocks could be temporary. The model implicitly assumes that oil price changes are expected to be permanent. This makes using later oil shocks inappropriate since expectations likely violated this assumption.

Second, a convenient way to introduce an oil shock is to model the economy on a balanced growth path (in which energy prices are constant) and then shock it with an oil shock. The 1970s is the most recent time period that matches these dynamics. That is, a long period of price stability, real energy prices were relatively constant for the 20 years prior to the 1970s, followed by an unexpected jump in the oil price. To summarize, I have calibrated to the early 1970s oil shocks because it is the only historical episode that arguably matches the model's assumptions of being on a balanced growth path when there is a large and exogenous change in the price of oil imports that agents perceive to be permanent.

One limitation with using the early 1970s oil shocks to pin down the model parameters is that they happened 40 years ago. It is possible that some of the parameter values could have changed over time. Even so, any meaningful inference from a calibrated growth model requires the assumption of parameter constancy. And the parameters can be constant at values calibrated from any episode along the equilibrium path, whether the episode is early or late. As a check on the assumption of parameter constancy, I analyze the effects of the 2003 oil shock in both the model and the data in online Appendix C.[21] In particular, I calculate the responses of fossil and green innovation to a change in the price of oil imports. The responses are similar in the model and the data, suggesting that the parameter values that govern these responses have not changed substantially over time.

The early 1970s oil shocks coincided with a decline in the capacity of US oil fields (Hamilton 2009) and with changes in energy and environmental policies. These events likely affected energy innovation incentives, and so it is important to account for them in the calibration strategy. In particular, the EPA was initiated on December 2, 1970, and with it came the authority for the federal government to implement and enforce environmental regulation. This major regulatory change launched the United States into a new era of environmental stewardship (Berman and Bui 2001). Examples of influential environmental regulation from the early 1970s include the Clean Air Act, which limited emissions from coal power plants

[20] See, for example, Levy (1979); Energy Information Administration (1979); Energy Modeling Forum (1982).

[21] As discussed earlier, I do not calibrate to the 2003 oil shock because energy prices and energy innovation are not stable for a sustained period preceding the 2003 oil shock, suggesting that the assumption that the economy was on a long-run balanced growth path prior to the shock is imperfect. Moreover, after the 1970s, agents learned that energy prices are uncertain, and they formed expectations over future energy prices.

and oil refineries, and the Clean Water and Safe Drinking Water Acts, which placed restrictions on fossil energy companies' hazardous waste. Congress also passed a set of health and safety regulations in underground coal mines which reduced mining labor productivity (Bohi and Russell 1978).

In addition to this new era of environmental protection, the government implemented a series of oil price controls and windfall profits taxes on oil companies, which lasted from 1971 until 1982 when President Reagan deregulated the industry. These price distortions drove a wedge between the prices of imported and domestic oil and led to energy shortages. Furthermore, oil import restrictions were relaxed considerably in 1973 (Bohi and Russell 1978). The share of oil imports increased throughout most of the 1970s despite their rising cost.

All of these policies likely reduced the profitability of fossil energy extraction and the accompanying innovation incentives. To account for these coincident events in the calibration, I model effects of the policy changes together with the decline in the capacity of US oil fields as a negative productivity shock, ν, to fossil energy production:

$$F_t = \nu_t L_{ft}^{1-\alpha_f} \int_0^1 X_{fit}^{\alpha_f} A_{fit}^{1-\alpha_f} \, di. \tag{11}$$

Since the model is not sufficiently detailed to accurately incorporate each individual regulation change, I use the reduced-form productivity shock to capture the overall effects of the new regulation and the decline in oil capacity.

I jointly calibrate the parameters to match the data generated by the oil and productivity shocks of the early 1970s in the US economy with the data generated by the following experiment in the model:

Initial Balanced Growth Path (1961–1970): The economy is on a balanced growth path with respect to the price of oil imports and environmental and energy policies.

Shock Period (1971–1975): Two unexpected shocks realize: (i) the price of oil imports increases from its value on the balanced growth path; and (ii) a negative productivity shock affects domestic fossil energy production.

Environmental policy and the price of oil imports were relatively constant prior to the 1970s, allowing me to begin the experiment on a balanced growth path. I match this balanced growth path to data from 1961–1970. I begin the shock period in 1971 because the EPA was created in December of 1970, launching the United States into a new era of environmental regulation. Since this regulation was a major turing point in US environmental policy, it arguably knocked the United States off its balanced growth path and stimulated green energy investment and innovation. I measure the size of the oil shock by the observed percentage change in the average price of oil imports from 1971–1975 relative to its average value from 1961–1970. Both shocks are unexpected by the agents on the balanced growth path since they were unprecedented in the data. Machine production decisions are made prior to the realization of the shocks, while scientist and labor decisions are made after the shocks realize.[22]

I construct moments from this experiment so that the model matches the innovation incentives that coincided with the oil shocks and regulatory changes. Four important moments are the values of fossil energy production and oil imports (as shares of GDP) in both the balanced growth path and in the shock period. As shown in equation (10) and discussed in Section II, the values of fossil and green energy production ($P_f F$ and $P_g G$) are primary determinants of the innovation incentives in each of these sectors. However, data on the value of green energy production is not available. But one important component of the value of green energy production is the value of imported oil and data is available for the value of imported oil. Specifically, equation (12) (derived from the first-order conditions for the final good producer, see online Appendix A) shows that $P_g G$ is directly proportional to the value of the composite comprised of oil imports and fossil energy, $P_{\tilde{F}} \tilde{F}$:

$$P_{gt} G_t = P_{\tilde{F}t} \tilde{F}_t \left(\frac{P_{\tilde{F}t}}{P_{gt}} \right)^{\varepsilon_e - 1}. \tag{12}$$

The CES properties of the production functions imply that the value of this composite equals the sum of the values of fossil energy production and oil imports: $P_{\tilde{F}f} \tilde{F}_t = P_{ft} F_t + P^*_{ot} O^*_t$. Therefore, the value of oil imports is also important for capturing innovation incentives.

Two more relevant moments are the research expenditures on fossil and green energy as a fraction of total research expenditures. The energy research data are not available until 1972, so I construct the empirical averages from 1972–1975. Research expenditures in the data correspond to the wage multiplied by the number of scientists in the model. Scientist market clearing implies that the scientists' wages are equated across all sectors. Therefore, the fraction of research expenditures in fossil energy in the data corresponds to the fraction of scientists in fossil energy in the model (and likewise for green energy research). Table 2 reports the empirical values of the moments in both the balanced growth path and the shock period. Additionally, I target the annualized long-run growth rate of GDP per capita of 2 percent.

This process yields seven moments (those listed in Table 2 plus the long-run growth rate of per capita GDP) for the six parameters and the productivity shock, ν. For each set of parameters, I solve the model, compute the moments, and compare them with the moments in the data. I use the Nelder-Mead simplex algorithm (Nelder and Mead 1965) to minimize the sum of the square of the residuals between the empirical and model values of the moments.[23] The model fits the data very closely; the minimized distance is 2.2×10^{-21}. Online Appendix C evaluates the fit of the model against five non-targeted moments. The values of these moments are relatively similar in the model and the data, suggesting that the model's fit is

[22] The empirical evidence supports these timing assumptions. The change in the fraction of fixed assets in the fossil energy sector (relative to total fixed assets) is very small from 1971–1975. In contrast, the fraction of energy research expenditures relative to total research expenditures almost doubles from 1972 to 1975.

[23] Specifically, I modify routine 10.4 in Press et al. (1992).

Table 2—Data in the Balanced Growth Path and Shock Period

	Balanced growth path	Shock period
Fossil energy production share	1.9	2.1
Oil imports share	0.2	0.8
Percent of R&D expenditures in fossil	—	2.1
Percent of R&D expenditures in green	—	3.4

Notes: The values on the balanced growth path are equal to the empirical average from 1961–1970. The values during the shock period are equal to the empirical average from 1971–1975.

Source: Author's calculations based on data from the BEA, EIA, and NSF Survey of Industrial Research and Development

reasonably strong. Online Appendix D reports bootstrapped standard errors for the parameters calibrated from the method-of-moments procedure. The standard errors suggest a reasonable degree of precision for most of the parameter estimates.

While all of the parameters are jointly determined, the shares of fossil energy production and oil imports on the initial balanced growth path are pinned down primarily by the CES distribution parameters, $\delta_{\tilde{F}}$ and δ_y. The movements in these shares are largely governed by the productivity shock, ν, and the elasticity of substitution between fossil energy and oil imports, ε_f. For example, if fossil energy and oil imports are more substitutable, then the oil shock leads to a larger increase in demand for fossil energy, which leads to a bigger increase in the fossil energy price, quantity, or both. Hence, increases in this substitution elasticity result in a larger increase in fossil energy production (as a share of GDP) in response to the oil shock.

The research expenditure moments primarily pin down the level of diminishing returns, η, and the labor share in green energy, $1 - \alpha_g$. The price elasticity of demand for green machines is $1/(1 - \alpha_g)$. All else constant, increases in labor share reduce the price elasticity of demand. Less elastic demand increases the machine producer's optimally chosen machine price, raising the returns to innovation (see online Appendix A for the derivation and further discussion). Parameter γ determines the long-run growth rate.

The calibration strategy does not pin down the strength of the cross-sector spillovers, ϕ. All else constant, this parameter determines the relative levels of energy technology on the balanced growth path. For example, if the cross-sector spillovers are relatively weak (ϕ is small), then the only stable balanced growth paths are corner solutions in which all innovation occurs in a single energy sector. In this case, the levels of fossil and green technology would grow farther and farther apart along the balanced growth path. Alternatively, if the cross-sector spillovers are relatively strong (ϕ is big), then there exists a stable interior balanced growth path in which innovation occurs in both fossil and green energy. In this case, the ratio of fossil to green technology would be constant along the balanced growth path. Moreover, the closer this constant ratio is to unity, the stronger the cross-sector spillovers. Data on energy innovation (and thus on technology) are not available on the balanced growth path of the 1960s, making it difficult to pin down a value for ϕ.

However, the data do provide suggestive evidence that the value of ϕ is greater than 0.2, the cutoff for which interior balanced growth path in which agents innovate in both energy sectors is stable. If instead $\phi < 0.2$, then this would imply that green innovation was zero along the balanced growth path of the 1960s, since fossil innovation was clearly greater than zero during this time. However, major US companies were involved in green R&D in the 1960s. For example, General Electric designed the first boiling water nuclear reactor in 1960 and invented the LED lightbulb in 1962, while Sharp Corporation invented practical silicon photovoltaic modules in 1963 (an early advance in solar technology). Additionally, in the early 1970s, green innovation expenditures were over half of all energy innovation expenditures. It is highly unlikely that green innovation would go from nonexistent to over half of all energy innovation in such a short time frame. Combined, these two pieces of evidence imply that the cross-sector spillovers must be sufficiently strong so that positive innovation occurred in both fossil and green energy along the 1960s' balanced growth path. I set $\phi = 0.5$ in the main specification. In online Appendix F, I report the main results for a range of values of $\phi > 0.2$.

Labor share in green energy is 0.09, implying that green energy is a very capital-intensive sector. Consistent with this calibration, green energy technologies, such as nuclear, solar, and, particularly energy efficiency, are all very capital intensive. The elasticity of substitution between fossil energy and oil imports, ε_f, is considerably higher than that between green energy and the composite comprised of fossil energy and oil imports, ε_e, (6.24 compared to 1.5), suggesting that fossil energy is a better substitute for oil imports than green energy. This is intuitive since one component of fossil energy is domestically produced oil, which is a perfect substitute for imported oil. The diversities of the energy sectors, ρ_f and ρ_g, are both small compared to the nonenergy sector.

The calibrated value of the distribution parameter, δ_y, is very small. This is because the elasticity of substitution between energy and nonenergy inputs in the production of output, ε_y, is also very small, ($\varepsilon_y = 0.05$). The value of the quantity that is economically relevant for the optimal allocation between energy and nonenergy inputs, $\left(\delta_y/(1-\delta_y)\right)^{\varepsilon_y}$, (see equation (A2) in online Appendix A) is considerably larger $\left(\left(\delta_y/(1-\delta_y)\right)^{\varepsilon_y} = 0.01\right)$.

Additionally, the calibrated size of the productivity shock, ν, is 0.64, suggesting that the combined effects of the environmental regulations, the distortions created by price controls and import policies, and the declining capacity of US oil fields substantially reduced productivity in fossil energy. This result relates to the literature linking the productivity slowdown to increased environmental regulation in the 1970s (e.g., Gray 1987). To comply with the regulations, firms must divert resources away from output production, lowering productivity.

E. *Comparison to Empirical Studies*

As an additional check on both the calibration and the model specification, it is useful to compare the implications of the calibrated quantitative model with the empirical literature on energy prices and innovation. Both Popp (2002) and Aghion et al. (2016) calculate the elasticity of green energy patents with respect to a change in energy prices. Popp (2002) estimates this elasticity from aggregate US time series data from 1970–1994 on fossil energy prices and green energy patents in 11 energy technologies. Six of these technologies relate to energy supply (such as solar) and five to energy demand (such as the reuse of industrial waste heat). Aghion et al. (2016) focus on the automobile industry. They use a cross-country, firm-level panel on green car patents (e.g., hybrid vehicle technologies) and tax-inclusive gas prices to estimate the price elasticity of R&D in green car technologies. The five-year price elasticity of green patents is 0.21 in Popp (2002) and is 3.7 in Aghion et al. (2016).[24]

To compare these empirical results with the present paper, I rewrite the technology accumulation equation for green technology (equation (4)) as the sum of the existing green technology stock and new green ideas, $\mathcal{I}_g$:

$$A_{gt} = A_{gt-1} + \mathcal{I}_{gt} \quad \text{where} \quad \mathcal{I}_{gt} = \gamma \left(\frac{S_{gt}}{\rho_g} \right)^{\eta} A_{t-1}^{\phi} A_{gt-1}^{1-\phi}. \tag{13}$$

New green ideas are the flow input into technology and, thus, correspond to green patents in the data. Let $P_{\tilde{F}}$ be the tax-inclusive price of the composite comprised of fossil energy and foreign oil (see equation (A3) in online Appendix A). The (one-period) elasticity of new green ideas with respect to a change in $P_{\tilde{F}}$ from the introduction of a carbon tax is

$$\epsilon = \left(\frac{\mathcal{I}_{gt^*} - \mathcal{I}_{gt^*-1}}{\mathcal{I}_{gt^*-1}} \right) \left(\frac{P_{\tilde{F}t^*-1}}{P_{\tilde{F}t^*} - P_{\tilde{F}t^*-1}} \right), \tag{14}$$

where t^* is the period in which the carbon tax is introduced.[25]

The value of this elasticity in the model is 1.7. This estimate is between the estimates in Popp (2002) and Aghion et al. (2016). One explanation for why the model value of the elasticity is larger than the estimate in Popp (2002) is that the green innovation in the sectors covered in Popp's study is less responsive to changes in $P_{\tilde{F}}$ than green innovation in the average sector. However, a second explanation for the different elasticity is the source of the change in $P_{\tilde{F}}$. Popp's calculation uses aggregate variation in fossil energy prices from oil shocks (or similar macroeconomic events) instead of from a carbon tax. While both oil shocks and carbon taxes increase incentives for green innovation, oil shocks also increase incentives for fossil innovation. If there is crowd-out between fossil and green innovation, then the price elasticity of green innovation will be smaller when the price change is caused by an oil shock than when it is caused by a carbon tax. Consistent with this hypothesis, the model elasticity of green ideas from an increase in $P_{\tilde{F}}$ from an oil shock is 1.3, approximately 25 percent smaller than the elasticity from a carbon tax. In a related empirical patent study, Popp and Newell (2012) find suggestive evidence of this crowd-out within energy supply technologies (such as oil refining and solar).

One explanation for why the model value of the elasticity is smaller than the estimate in Aghion et al. (2016), is that innovation in green car technologies is more responsive than average green innovation to changes in the fossil energy price. Some of the variation in gas prices comes from differences in the gas tax and some

[24] Both Popp (2002) and Aghion et al. (2016) estimate a dynamic specification, which make it possible to compute the five-year elasticity. See Table 4 in Popp (2002) and Table 10 in Appendix C in Aghion et al. (2016).

[25] Prior to period t^*, the economy is on a balanced growth path.

comes from oil shocks. However, since the automobile industry does not supply fossil energy, price changes from oil shocks and carbon taxes should create similar incentives for innovation in green car technologies. Thus, differences in the elasticity estimates due to crowd-out are not as likely in this case.

IV. Results

I perform two exercises to fully explore the interactions between endogenous innovation and climate policy. In both exercises, the economy begins on the same baseline balanced growth path, but innovation is endogenous in the first and exogenous in the second. I introduce constant carbon taxes in the 2015–2019 time period. I choose the size of the tax in each exercise to achieve a 30 percent reduction in emissions from the baseline balanced growth value in 20 years, that is, by the 2030–2034 time period. The size of the tax necessary to achieve the emissions target is different for economies with endogenous versus exogenous innovation.[26]

The endogenous-innovation model is my benchmark model. Machines, workers, and scientists all adjust in response to the tax. The exogenous-innovation model has the endogenous innovation channel shut down. Unlike in the endogenous-innovation model, only machines and workers adjust in response to the tax; the scientists (and hence the levels and growth rates of technology) are fixed at their baseline balanced growth values.

A. *Carbon Tax: The Role of Endogenous Innovation*

The carbon taxes required to achieve the emissions target are 30.3 and 24.5 in 2013 dollars per ton of CO_2 in the exogenous- and endogenous-innovation models, respectively. The required carbon tax is 19.2 percent lower when innovation is endogenous. The intuition for this result is that regardless of whether innovation is endogenous, the carbon tax operates through prices to shift demand from fossil to green energy, reducing emissions. However, when innovation is endogenous, this shift in demand increases green innovation and decreases fossil innovation. Over time, this change in innovation reduces the marginal cost of producing green energy relative to fossil. This lowers the relative price of green to fossil energy, creating stronger incentives for the final-good producer to switch from fossil to green. Thus, endogenous innovation amplifies the price incentives created by the carbon tax, implying that the same reduction in emissions can be achieved with a smaller tax.

An analogous interpretation of this result is that endogenous innovation increases the emissions reduction from a given-sized carbon tax. In particular, if the carbon tax is \$30.3 per ton, then endogenous innovation increases the percent reduction in emissions by close to 5 percentage points (from 30 percent to 34.6 percent). A policy implication of these results is that if the government designs a cap-and-trade

[26] In both exercises, I hold the value of the productivity shock and the foreign oil price constant. The productivity shock equals unity. The foreign oil price equals 2.15 times the domestic fossil energy price on the balanced growth path, its average empirical relationship from 2001 to 2010.

system to achieve a target permit price (perhaps because a carbon tax is politically infeasible), then endogenous innovation implies that the government should issue fewer permits in order to achieve its price target. This implication is particularly relevant for the case of the EU-ETS where, for several reasons, governments over-allocated permits and the price fell below the desired level.

The finding that the carbon tax necessary to achieve the emissions target is 19.2 percent lower when innovation is endogenous is sensitive to both the size of the targeted reduction in emissions and the time frame in which the reduction must be achieved. Online Appendix E analyses the effects of innovation for different-sized emissions targets and different time frames. In particular, the effect of endogenous innovation on the size of the carbon tax is smaller if the target is more stringent or the time frame is shorter. More stringent targets and shorter time frames force agents to rely less on technological advances and more on shifts in production factors (i.e., workers and machines) to achieve the emissions target. This switch reduces the role of endogenous innovation and its accompanying effects on the size of the required carbon tax.

Table 3 provides more details on the mechanisms driving the effects of endogenous innovation. Column 2 of Table 3 reports the values on the baseline balanced growth path. Each row in columns 3–5 reports a measure of the treatment effect; they show the percentage difference from the baseline in each of the variables after 20 years (i.e., in the 2030–2034 time period) and on the long-run balanced growth path under the carbon tax. For example, the first row of column 4 implies that when innovation is endogenous, fossil energy scientists are 60.5 percent lower than their baseline value after 20 years under the tax. Table 3 does not include a column for exogenous innovation on the long-run balanced growth path because there are no transitional dynamics when innovation is exogenous; the values after 20 years equal the values in the long-run balanced growth path under the carbon tax.

The carbon tax leads to large shifts in fossil and green innovation and relatively small movements in nonenergy innovation (innovation segment of Table 3). After 20 years, the tax reduces fossil innovation by 60.5 percent, increases green innovation by 53.3 percent, and increases nonenergy innovation by 0.4 percent.[27] These results suggest that the increased green innovation comes at the expense of (i.e., crowds out) fossil innovation and not nonenergy innovation. Since fossil and green energy are gross substitutes, the tax shifts demand from fossil to green energy, increasing the green innovation incentives. In contrast, because the energy and nonenergy inputs are almost perfect complements, the effects of the tax on the value of nonenergy production and the corresponding innovation incentives are small. These movements in innovation affect relative technology. After 20 years, the ratio of green to fossil technology is 44.5 percent higher than in the baseline. On the long-run balanced growth path, this ratio is more than double its baseline value.

The prices segment of Table 3 shows the effects of the tax on relative prices. When innovation is endogenous, the relative price of green compared to fossil energy falls

[27] While the overall number of scientists is fixed, the sum of the percentage change of the number of scientists in each sector does not equal zero because the baseline levels are very different.

Table 3—Effects of a Carbon Tax That Achieves a 30 Percent Emissions Reduction in 20 Years

		Percent difference from the baseline		
	Baseline level	Exogenous innovation (in 20 yrs.)	Endogenous innovation (in 20 yrs.)	Endogenous innovation (long run)
Innovation				
Fossil scientists: S_f	1.5e-04	0	−60.5	−29.9
Green scientists: S_g	1.0e-04	0	53.3	23.8
Nonenergy scientists: S_n	9.7e-03	0	0.4	0.2
Relative technology				
Green to fossil: $\frac{A_g}{A_f}$	0.4	0	44.5	144.6
Green to nonenergy: $\frac{A_g}{A_n}$	0.9	0	16.9	39.3
Relative prices				
Green to fossil: $\frac{P_g}{P_f}$	1.1	0.2	−7.0	−17.1
Green to nonenergy: $\frac{P_g}{P_n}$	1.4	0.6	−1.0	−2.6
Energy to nonenergy: $\frac{P_e}{P_n}$	3.9	14.9	13.0	14.6
Relative production				
Green to fossil: $\frac{G}{F}$	1.4	78.0	79.2	112.9
Energy to nonenergy: $\frac{E}{N}$	0.01	−0.7	−0.6	−0.7
Relative wages				
Scientist to worker: $\frac{w_s}{w_l}$	2.7	—	−0.1	−0.1
Climate				
Emissions	—	−30.0	−30.0	−36.9

Notes: The baseline is the balanced growth path with no carbon tax. This balanced growth path is the same in the endogenous- and exogenous-innovation models. The percent difference from the baseline under exogenous (endogenous) innovation in 20 years is the percent difference in the value of the variable in the exogenous-innovation (endogenous-innovation) model from its value in the baseline in the 2030–2034 time period. The long run refers to the long-run balanced growth path under the carbon tax. The values on the long-run balanced growth path under exogenous innovation are the same as the values in 20 years because there are no transitional dynamics when innovation is exogenous. Variable P_e is the tax-inclusive price of the CES composite of fossil energy, green energy, and oil imports, E.

by 7.0 percent after 20 years and by 17.1 percent on the long-run balanced growth path. The fall in the relative price of green to fossil energy results from both the increase in green innovation and the decrease in fossil innovation. Increases in green innovation reduce the marginal cost of green energy production, reducing the relative price of green to fossil energy. Decreases in fossil innovation raise the marginal cost of fossil energy production (relative to the baseline), raising its price, and, thus, further reducing the relative price of green to fossil energy. In contrast, when innovation is exogenous, there is almost no change in the relative marginal costs of the different inputs, and relative prices are almost the same as on the baseline balanced growth path.[28] Therefore, almost all of the change in the energy prices in the endogenous-innovation model results from changes in technology.

The production segment of Table 3 reports the effects of the carbon tax on the production of the different intermediate inputs. At the 20-year mark, the changes in the relative quantities of green compared to fossil energy production are similar between the endogenous- and exogenous-innovation models because the carbon tax achieves the same reduction in emissions. However, the long-run effects are very different; on the new balanced growth path, the tax increases the ratio of green to fossil production by 112.9 percent in the endogenous-innovation model compared to by only 78.0 percent in the exogenous-innovation model. This difference arises because green technology keeps growing relative to fossil after the 20-year mark, further decreasing the relative price of green energy and, thus further increasing the final-good producer's green energy demand. Unlike fossil and green energy production, the changes in the ratios of energy to nonenergy production are almost zero. Since the elasticity of substitution between energy and nonenergy inputs is close to zero, the final-good producer must substitute green energy for fossil energy and oil imports to reduce emissions, instead of substituting nonenergy inputs for energy inputs.

The relative wage segment of Table 3 reports the effects of the carbon tax on the return to supplying labor as a scientist, w_s, relative to the return to supplying labor as a worker, w_l. The carbon tax has almost no effect on the relative returns; on the new long-run balanced growth path, the return to scientists relative to the return to workers is only 0.1 percent smaller than its value in the baseline. This near constancy suggests that the carbon tax would not lead to substantial changes in the relative quantities of scientists and workers, supporting the assumption of fixed supplies of scientists and workers.

Finally, I calculate the CEV to quantify the gross welfare costs of the policy. The CEV is the uniform percentage increase in an agent's consumption in the baseline that is necessary to make him indifferent between the baseline and the carbon tax scenarios. The CEVs are -0.3 percent and -0.4 percent in the endogenous- and exogenous-innovation models, respectively.[29] Total consumption for all individuals in the United States from 2008–2012 was approximately \$53,671 billion (2012 dollars), so the CEVs in the endogenous- and exogenous-innovation models equal approximately $-$\$172 and $-$\$225 billion, respectively.[30]

Endogenous innovation reduces the gross welfare cost of the policy by 0.1 percentage points. Endogenous innovation affects the gross welfare costs through three partially offsetting channels. First, the carbon tax is smaller when innovation is endogenous; hence, the accompanying gross distortionary cost is smaller. Second, green energy is technologically behind fossil energy when the government implements the tax. Thus, the tax shifts energy production to a less productive

[28] Energy prices under the tax in the exogenous-model are not identical to their baseline values because the general equilibrium effects lead to small changes in the wage. These changes have different effects on the marginal cost of production in the different sectors, which, in turn, affect relative prices.

[29] To calculate the CEV, I set the annual rate of time preference to 1.5 percent and the intertemporal elasticity of substitution to the standard value of one half, $\theta = 1/2$.

[30] See BEA personal consumption expenditures.

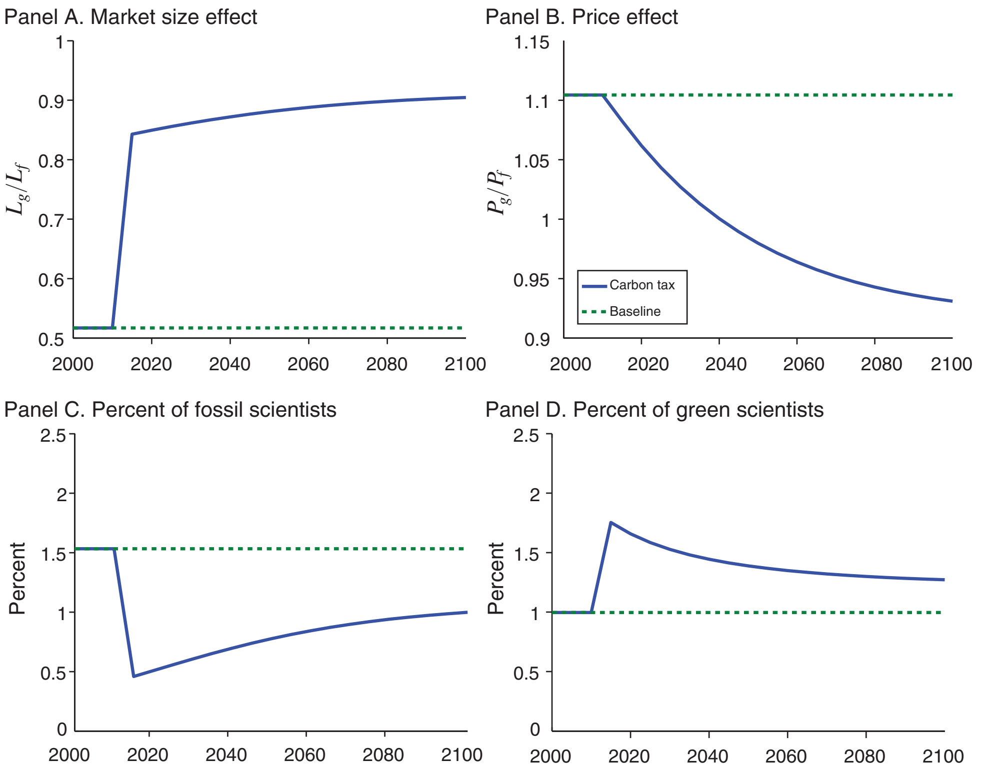

Figure 1. Dynamic Effects of a Carbon Tax

sector. Endogenous innovation reduces these productivity losses as green technology catches up to fossil. Third, the shift in innovation from fossil to green energy reduces the aggregate growth rate along the transition path to a new long-run equilibrium. This temporary reduction in growth raises consumption costs and mutes the gross welfare gain from endogenous innovation.

This paper is focused on the key mechanisms driving the interaction between innovation and climate policy. However, the results have interesting and opposing implications for the effects of endogenous innovation on the size of the optimal carbon tax. Endogenous innovation reduces the size of the tax necessary to achieve a given abatement target, implying a smaller optimal carbon tax. Working in the other direction, endogenous innovation also reduces the marginal abatement costs, raising the optimal abatement target, implying a larger carbon tax. Determining which of these two effects dominate is beyond the scope of this paper and is an interesting avenue for future research.

B. *Dynamics*

I discuss the dynamics along the transition to the new balanced growth path, focusing explicitly on the general equilibrium forces driving innovation. Figure 1 plots the dynamics with respect to four key variables in response to the carbon tax: (i) the market size of green relative to fossil energy (measured by the relative levels of employment, L_g/L_f), (ii) the price of green relative to fossil energy, P_g/P_f, (iii) the percent of fossil energy scientists, and (iv) the percent of green energy scientists. The tax shifts demand from fossil to green energy, leading to an immediate jump in the green energy market size (panel A of Figure 1) and in the percents of fossil and green energy scientists (panels C and D of Figure 1). The surge in green innovation relative to fossil leads to a gradual improvement in the relative level of green technology, which reduces the relative price of green energy over time (panel B of Figure 1). The fall in the relative price slowly decreases green innovation incentives, causing green energy scientists to asymptote to a new equilibrium level, below their initial jump but above their value on the original balanced growth path.

C. *Comparison to Earlier Work*

AABH find that climate policy and endogenous innovation tip the economy to a new long-run equilibrium where green technology grows and fossil technology is constant. The results in the present paper indicate somewhat smaller effects of endogenous innovation on climate policy outcomes than in AABH. These different findings are primarily due to two key parameters: the diminishing returns to innovation, η, and the strength of the cross-sector technology spillovers, ϕ. Stronger diminishing returns to innovation (lower η) create incentives to spread scientists across both the fossil and green energy sectors. This spreading reduces the effect of a carbon tax on the direction of technical change. Stronger cross-sector spillovers (higher ϕ) reduce the path dependence in innovation. Green technology accumulates faster than fossil technology in response to the carbon tax. If some of the new green discoveries are applicable to fossil energy, then these spillovers indirectly encourage innovation in fossil energy. The calibration in the present paper uses middle values for both η and ϕ: $\eta = 0.79$, $\phi = 0.5$, while AABH use $\eta = 1$ and $\phi = 0$. This implicit parameter choice in AABH increases the role of endogenous innovation relative to the present paper.

It is also useful to compare the results of the present paper to the results from three closely related papers on endogenous innovation in integrated assessment climate-economy models: Goulder and Schneider (1999), Popp (2004), and Gerlagh (2008). In their seminal paper, Goulder and Schneider develop both analytical and numerical climate-economy models with endogenous innovation. While their models are largely qualitative, they find that the inclusion of endogenous innovation increases the amount of abatement from a given sized carbon tax, consistent with the present paper.

Popp (2004) modifies the DICE model of climate change (Nordhaus and Boyer 2000) to include endogenous innovation in a single energy sector and quantifies its effects on climate policy outcomes. Relative to the present paper, Popp (2004) finds that including endogenous energy innovation has very small implications for the size of the carbon tax necessary to achieve a given emissions target, but considerably larger effects on welfare. Gerlagh (2008) develops a model that allows for endogenous innovation in multiple sectors. Relative to the present paper, he finds larger effects of endogenous innovation on the size of the carbon tax necessary to achieve a given climate target.[31]

These differences largely arise because the models in the earlier work are more complex in some ways but are reduced form in other ways. For example, Popp (2004) focuses on the effects of endogenous innovation on the optimal time path of the carbon tax. Solving for this optimal time path comes at the expense of incorporating general equilibrium features such as the production of fossil energy, endogenous energy prices, a green energy sector, and endogenous innovation in more than one sector. Similarly, Gerlagh (2008) does not directly model a green energy sector and his calibration procedure assumes that the economy is in steady state with respect to energy (and other variables) from 1970–1990. Such an assumption is at odds with the data on energy prices and innovation and Gerlagh stresses that a more robust calibration procedure is essential for future work.

Unlike much of the previous environmental literature, the present paper specifically models the general equilibrium effects from endogenous innovation in each of two energy sectors (green and fossil) and in a third sector comprising the rest of the economy. These features influence the effects of endogenous innovation on climate policy outcomes along three important dimensions.

First, the potential for innovation in fossil, green, and nonenergy sectors is important for obtaining a plausible calibration that applies to the whole economy. This three-sector design facilitates a direct mapping to the data on fossil, green, and nonenergy R&D, which can be difficult to obtain otherwise. Moreover, the model framework allows for the distinction between the innovation incentives offered by the carbon tax versus those offered by higher energy prices due to non-tax induced changes in energy supply or demand. This distinction is crucial for obtaining a realistic calibration based on historical data in which higher energy prices occurred because of supply or demand changes instead of from a carbon tax.

Second, the general equilibrium, three-sector framework fully endogenizes the relative price of green to fossil energy. This relative price is the primary determinant of firms' energy choices and, hence, of aggregate emissions. The relative price depends on the levels of innovation in both the fossil and the green energy sectors. If the policy causes green innovation to increase above its baseline level, then the marginal cost of producing green energy falls, reducing the relative price of green to fossil energy. If the policy also causes fossil innovation to decrease below its baseline level, then the marginal cost of producing fossil energy rises (relative to the baseline), causing the relative price of green to fossil energy to fall further. The quantitative impact of the reduced fossil energy innovation on this relative price is considerable and clearly captured within this three-sector, directed technical change framework.

[31] Specifically, Popp (2004) compares the size of the carbon tax necessary to restrict emissions to their 1995 levels in his model with and without endogenous energy innovation. The difference in the size of the tax is less than 1 percent. Additionally, he finds that including endogenous energy innovation increases welfare under the optimal policy by 9.4 percent. Gerlagh (2008) compares the size of the carbon tax necessary to stabilize the atmospheric carbon concentration at 450ppmv. He finds that endogenous innovation reduces the size of the carbon tax necessary to achieve this stabilization target by a factor of two. Some of the differences with earlier work could partially result from these differences in the simulated emissions and climate targets.

Third, the three sectors imply that increased green innovation can crowd out fossil innovation and/or nonenergy innovation. These two dimensions for crowd-out have substantially different implications for both the effectiveness and gross welfare cost of the carbon tax. Increased green innovation at the expense of fossil innovation amplifies the impact of green innovation on the relative price of green to fossil energy, increasing the emissions reduction from the carbon tax. In contrast, increased green innovation at the expense of nonenergy innovation could result in a larger reduction in economic growth, amplifying the gross welfare costs of the policy.[32]

D. *Sensitivity Analysis*

I conduct sensitivity analysis across all the model parameters. Specifically, I analyze the percent that endogenous innovation reduces the size of the carbon tax required to achieve the emissions target for different parameter perturbations. The results are particularly sensitive to changes in the diminishing returns to innovation, η. Weaker diminishing returns (bigger η) increase the amount that agents raise green innovation in response to the carbon tax, thus increasing the effect of endogenous innovation on the size of the carbon tax.

The results are surprisingly insensitive to changes in the substitution elasticity between green energy and the composite comprised of fossil energy and foreign oil, ε_e. All else constant, lower values of ε_e reduce the shift in demand from fossil to green energy in response to the tax. A smaller demand shift leads to a smaller change in innovation, decreasing the effects of endogenous innovation on the size of the carbon tax. However, the magnitude of this decrease is reasonably small; even if $\tilde{F}$ and G are almost Cobb-Douglas ($\varepsilon_e = 1.1$), endogenous innovation still reduces the size of the carbon tax by 17.4 percent. The reason for this small effect is that matching the targeted moments with lower values of ε_e requires weaker diminishing returns to innovation. As the strength of the diminishing returns to innovation falls (η approaches unity), the effects of endogenous innovation on the size of the carbon tax increase, partially offsetting the decrease from the smaller substitution elasticity. Thus, the effects of changes in ε_e are smaller than one might expect when the model is required to match the historical record. Online Appendix F reports the detailed results from the sensitivity analysis.

V. Conclusion

This paper develops a general equilibrium model to quantify the response of technology, prices, and other macroeconomic aggregates to climate policy. Building on the directed technical change literature, I model an economy in which scarce innovation resources can be allocated toward fossil energy, green energy, and nonenergy intermediate inputs. I calibrate the model parameters using data from the natural experiment on energy prices and innovation from the oil shocks in the first half of

[32] While both types of crowd-out are possible, I find that green energy innovation almost exclusively crowds out fossil innovation, and not nonenergy innovation (see Section IVA).

the 1970s. I then use this empirically grounded model as a quantitative laboratory in which to study climate policy.

A key result is that endogenous innovation amplifies the price incentives created by the carbon tax. The tax operates through prices to shift innovation from fossil to green energy. This shift in innovation raises green technology compared to the baseline balanced growth path, decreasing the green energy price. Similarly, fossil innovation falls compared to the baseline balanced growth path, increasing the fossil energy price. These additional price movements reduce the size of the carbon tax required to attain a given abatement target. Specifically, endogenous innovation lowers the size of the carbon tax necessary to achieve a 30 percent emissions reduction in 20 years by 19.2 percent.

Overall, the results imply that endogenous innovation has considerable effects on climate policy outcomes. Shifts in innovation in response to the carbon tax lower the relative price of green to fossil energy by approximately 7 percent in the short run and 17 percent in the long run. Moreover, the relative level of green to fossil technology stabilizes at approximately two and a half times its value on the baseline balanced growth path.

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