Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution*

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02.09.2024

Abstract

We investigate the short- and long-term effects of a natural gas boom in an economy where energy can be produced with coal, natural gas, or clean sources and the direction of technology is endogenous. In the short run, a natural gas boom reduces carbon emissions by inducing substitution away from coal, but it also discourages innovation in clean energy. This delays and can even prevent the energy transition to zero carbon. We calibrate our model to the US electricity sector and find that the technology response to the shale gas boom results in a significant increase in long-run emissions. While the IRA can help the US economy avoid a

fossil-fuel trap, the natural gas boom leads to a decline of innovation in renewables for decades even with the IRA. Overall, the shale gas boom reduces social welfare, whereas, combined with the appropriate policy responses, it could have increased welfare substantially.

Keywords: climate change, director technological change, energy, environment, natural gas, shale gas, Inflation Reduction Act.

JEL Classification: O30, O41, O44, Q33, Q43, Q54, Q55

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We thank Stephie Fried, Derek Lemoine, Hannes Malmberg, Torsten Persson, and Fabrizio Zilibotti for helpful comments and suggestions. We thank seminar and conference participants at many institutions for comments and suggestions. We thank Maria Alsina Pujols for excellent research assistance. We acknowledge funding from the Alfred P. Sloan Foundation through grant #G-2019-12323. Acemoglu gratefully acknowledges financial support from the Hewlett Foundation. Hémous acknowledges financial support from the SNF through grant IZSEZ0223868

1 Introduction

There is growing recognition that transitioning to cleaner, non-fossil sources of energy is an imperative for humanity to reduce and reverse damages from global temperature rises, which are now set to exceed the target of 1.5°C above preindustrial times established at the Paris Agreement. Because renewable energy sources such as wind and solar still face major intermittency challenges and lack sufficient infrastructure, an economically appealing alternative may be to work towards this transition by initially relying on "transition fuels" such as natural gas that generate fewer emissions (see e.g., Greenstone 2024; IEA 2019). The final declaration of the COP28, for example, "recognizes that transitional fuels can play a role in facilitating the energy transition."

The "US shale gas boom"—arguably the most notable change in the US energy sector over the last several decades—could thus be seen as an enabler of the much-needed energy transition. Thanks to advances in horizontal drilling and hydraulic fracturing methods, US production of natural gas from shale deposits increased more than twelvefold and overall natural gas production rose by 50% between 2007 and 2018, as depicted in Figure 1 Panel A. The macroeconomic, technological, and full environmental consequences of this shale gas boom have not been systematically studied.

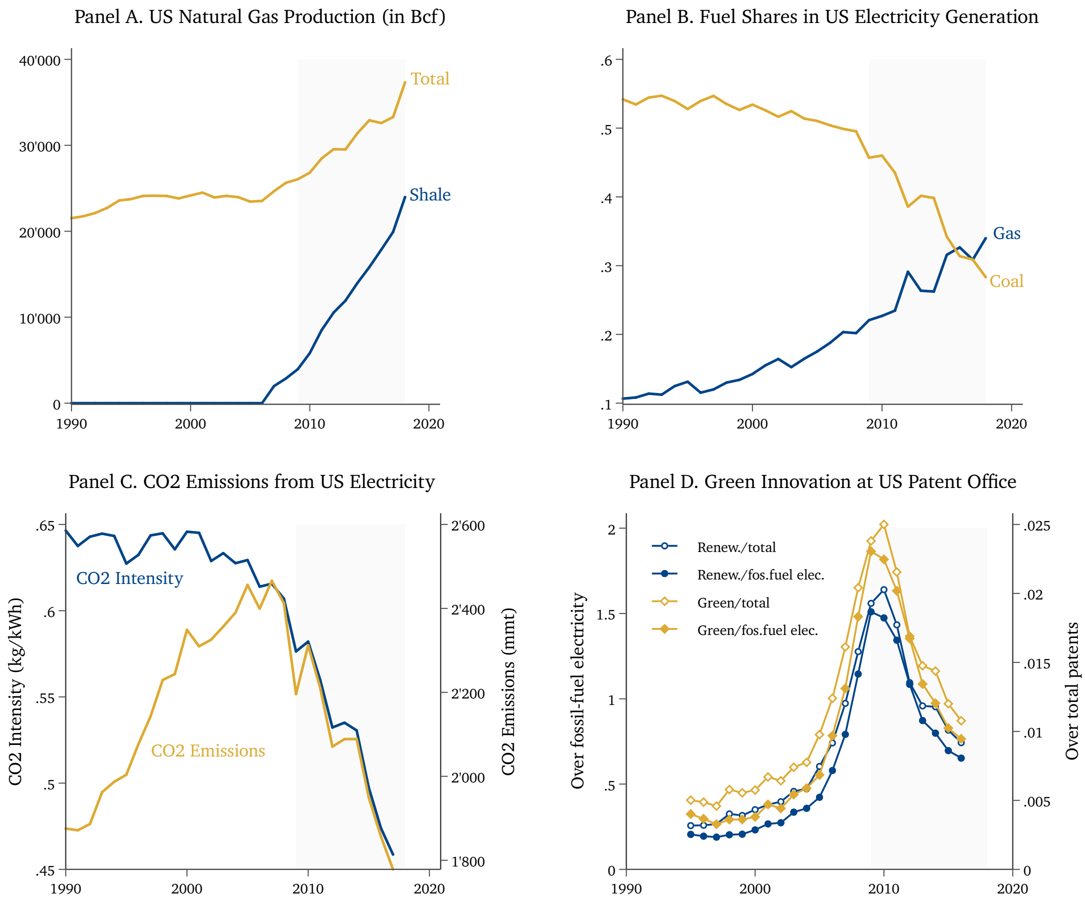
As shale gas production rose rapidly from 2009 onwards, natural gas displaced coal as the major source of fuel for the US electricity sector (see Figure 1.B). Because natural gas emits significantly less carbon than coal per unit of energy, US CO_2 emissions from the electricity sector peaked in 2007 and have been on a downward trend since (see Figure 1.C).

Yet, increasing usage of cleaner fossil fuels like natural gas has a darker side as well. Greater efficiency may increase emissions both statically and dynamically. Statically, a version of the Jevons's paradox applies as growing usage of cheaper natural gas corresponds to an increase in the energy efficiency of fossil fuels overall. The resulting increase in energy consumption can then lead to more, rather than less, emissions. Evidence in Figure 1.C, however, sheds doubt on the relevance of this static channel.

In this paper, we focus instead on the dynamic effects, which, to the best of our knowledge, are novel: greater energy efficiency of fossil fuels discourages innovation targeting cleaner (green) energy sources such as renewables and boosts long-run emissions. Interestingly, a significant slowdown in innovation in renewable has taken place concurrently with the shale gas boom, as shown in Figure 1.D: renewable patents in the US have declined from 1.9% of total patents in 2009 to only 0.8% in 2016. One contribution of our paper is to document this new stylized fact (see Popp, Pless, Hascic, and Johnstone 2022, for further evidence).

If the shale gas boom reduces emissions in the short-run but simultaneously displaces green innovation, then its overall impact on climate change mitigation and welfare are ambiguous and depend on the strength of the two opposing forces. Our major objective in this paper is to model, elucidate, and quantitatively evaluate these forces.

Figure 1—Natural Gas Production, Fuel Use, Emissions and Innovation in US Electricity



Note: This figure reports trends relevant to the US electricity sector. Panel A plots total and shale production of natural gas (data source: EIA). Shale gas production takes off from 2007 onward. Panel B reports the share of electricity from coal and from gas (data source: EIA). Gas overtakes coal after the shale gas boom. Panel C shows the CO_2 intensity of electricity production (left-axis) and CO_2 emissions (right axis), both drop following the shale gas boom (data source: US Environmental Protection Agency). Panel D reports ratios of either renewables or green (=renewables + nuclear + biofuel) patents over either fossil-fuel electricity or all patents (data source: PATSTAT). "Patents" here refer to USPTO patent applications. Innovation trends reverse after the boom.

With this purpose in mind, we build a parsimonious model of energy substitution and innovation. Energy can be produced with coal, natural gas, or a fully clean source, such as renewables. Natural gas has intermediate carbon emissions, and emissions create negative externalities both on domestic consumers and the rest of the world. The unique final good of the economy is produced by combining energy with other intermediates. Innovation is directed towards either fossil fuels or renewables, and can sustain long-run economic growth.

The model delivers the following insights. In the short run, a natural gas boom creates two opposing implications. First, there is a substitution effect, as natural gas is used increasingly in place of both dirtier coal-based energy and cleaner renewables. Under the plausible assumption that renewables are a small part of energy production initially, this substitution effect reduces carbon emissions. Second, and in opposition to this substitution mechanism, there is a scale effect. Namely, the shale gas boom reduces the overall price of energy which encourages energy consumption and thereby increases aggregate CO_2 emissions. The substitution effect dominates the scale effect and short-run emissions decline as long as natural gas is sufficiently clean compared to coal.

Long-run implications are more complex. The natural gas boom always reallocates scarce research inputs away from renewables towards fossil fuels, and consequently delays the energy transition. This effect may go beyond simple delay. We provide sufficient conditions for a "fossil-fuel trap" where the natural gas boom prevents the energy transition, while emissions would have converged to zero without the boom. With or without such a trap, the boom can reduce welfare. Overall, our theoretical analysis establishes how an unmanaged natural gas boom, such as the one unleashed by the recent shale gas boom, can increase long-run carbon emissions. This conclusion stands in contrast to what the economy could have achieved with optimal policy responses, which we also characterize.

Our theoretical results raise the possibility of paradoxical welfare effects from technological improvements in natural gas extraction. Are these mere theoretical possibilities or actually relevant for the current energy transition challenge? We explore this question in the last part of the paper. We undertake a quantitative analysis of both short-run and long-run implications of natural gas booms. We start by calibrating the model to the electricity sector in the United States. To do this, we collect generator-level micro data on power plants to quantify different components of generation costs, such as fuel resource costs, production input costs, and local pollution abatement expenditures. We combine these estimates with data on electricity production, fossil-fuel extraction productivity, current levels of policy support for different types of energy generations and innovations, aggregate data on output and profit margins, and estimates of the elasticity of substitution across fuels.

Our benchmark results suggest that, in the short-run, the shale gas boom led to an 11.5% decline in the CO_2 intensity of US electricity production and reduced emissions levels by about 4.5%. This underscores the possible environmental benefits from natural gas.

We then move to our main focus—the long-run implications from short-run substitution of natural gas for other types of energy. We estimate that an unmanaged shale gas boom leads to a persistent setback in green innovation and an associated increase in long-run CO_2 emissions. Whether the US falls into a fossil fuel trap as a result of the boom depends on our assumptions about business-as-usual (BAU) US energy policies. If BAU policies remain at levels observed from 2006-2020, the shale gas boom is predicted to push the US economy into a fossil fuel trap. In contrast, if we factor in the increase in US support for clean energy technologies introduced by the 2021 Inflation Reduction Act (IRA) and assume that this support will remain in place going forward, the US economy can avoid a fossil fuel trap and transition to green energy, albeit with a substantial delay compared to a world without the US shale gas boom. Our quantitative model matches several targeted moments, as well as important untargeted moments, such as the pre-and post-boom levels of green relative to fossil-fuel innovations. In our benchmark quantification, electricity sector emissions start rising from **2023** and are about 30-35% higher by 2100 as a result of the boom (depending on our assumptions about BAU policy). Our calibrated model predicts an overall (intertemporal) welfare loss from an unmanaged shale gas boom, equivalent to a 1.5% fall in yearly consumption. A permanent IRA could lower this welfare loss to about 0.4%.

We also demonstrate that the shale gas boom could have increased welfare considerably with optimal policies, which should have imposed greater subsidies to green technologies and higher carbon taxes. In fact, our benchmark estimates suggest that the shale gas boom has approximately *doubled* the potential welfare gains from adopting optimal climate policy, even when compared to a baseline with a permanent IRA in place.

Our paper contributes to a growing literature on the macroeconomics of climate change. A first strand develops "Integrated assessment models" (IAMs) for evaluating the macroeconomic and welfare impacts of climate change and various policies. This literature, pioneered by Nordhaus (e.g., 1994), has since grown considerably, including several recent macroeconomic works building on Golosov, Hassler, Krusell, and Tsyvinski (2014). This literature neither focuses on endogenous and directed technology nor investigates the long-run implications of natural resource booms.

Most closely related to our analysis is the literature on directed technical change (DTC, e.g., Acemoglu 1998, 2002) applied in the context of climate change and the energy sector. Several papers have incorporated induced innovation into models of climate change (see Gillingham, Newell, and Pizer 2008, for a review of the early literature). Smulders and de Nooij (2003), Hassler, Krusell, and Olovsson (2021) and Casey (2023) explore the consequences of DTC between energy-saving and energy-using technologies. We focus instead on DTC between clean and dirty technologies in energy production, building on and extending Acemoglu, Aghion, Bursztyn, and Hémous (2012), henceforth AABH, who characterize the optimal climate policy in the presence of DTC.[1] A number of papers have since extended AABH (see, e.g., Acemoglu, Akcigit, Hanley, and Kerr 2016, Hémous 2016, Aghion, Bénabou, Martin, and Roulet 2023). Fried (2018) looks at the implications of an exogenous oil price shock and Lemoine (2024) analyzes endogenous energy transitions when there are separate resource and non-resource inputs in energy production. We are not aware of any other work that either considers the effects of natural gas boom on the long-run direction of innovation and shows how such a boom can force the economy into a fossil-fuel trap. There is also no equivalent in this literature of our detailed quantitative exercise, which uses micro estimates from the electricity sector and also analyzes current policy issues, such as the IRA.[2]

We also build on existing computational energy models and empirical electricity sector analyses to study the shale gas boom. Quantitative models have found mixed net impacts owing to substitution and scale effects (see, e.g., McJeon et al., 2014, Gillingham and Huang 2019, Burtraw, Palmer, Paul, and Woerman 2012, and Brown and Krupnick 2010), while empirical studies have estimated significant short-run declines in the CO_2 emissions of electricity production as a result of the boom (e.g., Cullen and Mansur 2017; Fell and Kaffine 2018; Holladay and LaRiviere 2017; Linn and Muehlenbachs 2018). Loosely speaking, these papers correspond to the static component of our model and do not consider long-run

[1] Aghion, Dechezleprêtre, Hémous, Martin, and van Reenen (2016) provide empirical evidence for both DTC and path-dependence in the choice between clean and dirty technologies in the car industry. See also Popp (2002) or Calel and Dechezleprêtre (2016) for further evidence for DTC.

[2] Gentile (2024) considers the IRA in a DTC model focused on intermittency and storage technology. She also finds that, while the IRA improves welfare, it does not go far enough in incentivizing new technology development needed for the clean energy transition. This line of work adds to a growing literature that has studied the IRA in macroeconomic models with both exogenous technology and learning-by-doing effects (e.g., Casey, Jeon, and Traeger (2023), Bistline, Mehrotra, and Wolfram (2023), Arkolakis and Walsh (2023)).

technology implications, which are our main focus and contribution (though some of the models in McJeon et al., 2014, feature learning-by-doing). It is also worth noting that the empirical estimates in this literature are broadly in line with the static emission effects of the decline in natural gas prices in our model.

There is also an emerging literature investigating various broader consequences of the shale gas boom. Most closely related are Knittel, Metaxoglou, and Trindade (2016) and Daubanes, Henriet, and Schubert (2021), who model the possibility of carbon leakage through increased exports of coal and oil following the expansion of shale gas, and Gillingham and Huang (2019) and Henriet and Schubert (2019), who point out the possibility that shale gas may delay the deployment of renewables. In more recent work, Harstad and Holtsmark (2024) show that, in a setting with limited commitment, even a coalition of natural gas producing countries aiming to support optimal climate change policy may inadvertently harm global renewable energy production. These works do not study the effects of the shale gas boom on the direction of future technology,[3] which is our main contribution.

The rest of the paper is organized as follows. Section 2 presents evidence on the decline in green innovation and the role that natural gas prices have played in this redirection of technology. Section 3 develops our theoretical framework, and provides conditions under which a natural gas boom reduces emissions in the short run but increases them in the long-run because of the induced redirection of innovation. This section also characterizes optimal policy in the presence of a natural gas boom. Using data from the US electricity sector, Section 4 provides a quantitative analysis of the implications of our model, focusing especially on long-run consequences. Section 5 presents some extensions, and Section 6 concludes. Appendix A contains the proofs of our main results, additional empirical analyses, and various robustness exercises, and is included with the paper. Proofs of our secondary results can be found in the Supplementary Material available on our website at `https://www.econ.uzh.ch/en/people/faculty/hemous/research.html`.

2 The Shale Gas Boom and Green Innovations

The key building block of our study is the negative impact of natural gas (and specifically the shale gas revolution) on green innovations. A first contribution of our paper is to document

[3] Harstad and Holtsmark (2024) consider an extension with learning-by-doing but only in clean energy.

a large decline in green patents concurrently with the shale gas boom.

We rely on the World Patent Statistical Database (PATSTAT), which contains detailed information on patents from most patent offices in the world. We use the International Patent Classification (IPC) and the extended Cooperative Patent Classification (CPC) to identify green and fossil-fuel patents.[4] We refer to these patents as fossil-fuel patents (without emphasizing that they are for the electricity sector). Importantly, these *do not* include patents on extraction technologies such as hydraulic fracking and horizontal drilling that have been foundational to the shale gas boom.

Green innovations are identified as those in the group Y02E10 of the CPC, which correspond to renewable electricity (geothermal, hydro, tidal, solar thermal, photovoltaic and wind); those in Y02E30 for nuclear energy; and those in Y02E50 for biofuels and fuel from waste.[5] We assign patents to countries according to the location of the patent office at which they were filed. As more recent patent data are incomplete, our sample stops in 2016.

Figure 1.D in the Introduction plots patent applications at the USPTO, with year corresponding to the date of first filing. A sharp decline in the ratio of renewable to fossil-fuel patent applications after 2009-2010 is clearly visible. Figure 2 plots the same ratio for Canada, France and Germany, with Panel A for all patents, and Panel B for patents by domestic inventors (counting patents fractionally when inventors from multiple locations are listed). The same sharp decline from 2009-2010 is again visible. Note additionally that the reversal appears to have occurred a bit earlier for the United States and Canada, the two countries which first exploited shale gas, but is also quite sharp for France and Germany, even though these countries do not exploit shale gas. Nevertheless, innovation trends in France and Germany are relevant for our inquiry, for at least two reasons. First, European inventors sell globally and are therefore affected by North American shocks.[6] Second, the natural gas market in Europe was also impacted both by the US shale gas boom and by the greater availability of Russian gas via the Nord Stream pipeline. Appendix A.1 shows similar patterns

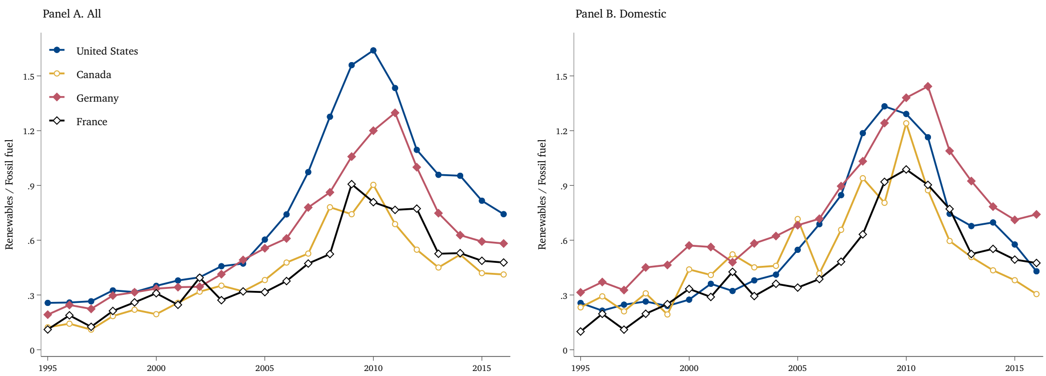
[4]Specifically, we build on Lanzi, Verdolini, and Hascic (2011) who identified IPC codes corresponding to fossil-fuel technologies for electricity generation. We count as fossil-fuel patents those with an IPC or CPC code in their list. The full list of codes is given in their Appendix A.1. We exclude the small fraction of patents without CPC codes from our analysis.

[5]Nuclear energy poses environmental and safety hazards, but does not generate greenhouse gases. Biofuels are used for transportation but also for electricity generations. Crucially, our green innovations exclude those aimed at reducing pollution from fossil-fuel electricity generation (Y02E20). They also do not include innovations aimed at improving the efficiency of the grid (Y02E40) and storage (Y02E60), since those are not technologies that compete directly with fossil-fuel technologies.

[6]Prior empirical work also confirms the role of global incentives in renewable innovation (e.g., Dechezleprêtre and Glachant 2014; Peters, Schneider, Griesshaber, and Hoffmann 2012).

for the ratio of green to fossil-fuel patents or for renewable patents relative to total patents. We note that the *level* of green patents also declined over this time period: in the US, the number of green patent filings (by domestic inventors) fell from a peak of 2955 in 2009 to 1755 in 2013 and further down to 860 in 2016.

Figure 2—Ratio of Renewables to Fossil-Fuel Patents



Note: This figure reports the ratio of renewables to fossil-fuel patents in the US, Canada, France and Germany (data source: PATSTAT). Patents are allocated to countries according to their patent office. In Panel A, we count all patents, while in Panel B, we only count patents by domestic inventors (allocating patents fractionally if inventors from multiple countries are listed). The reversal in innovation occurs in all four countries.

While our theory focuses on the effects of the shale gas revolution for innovation incentives, these incentives are also impacted by various other factors. To confirm the central role of natural gas prices and obtain estimates that correspond to the elasticity of green innovation to natural gas prices, we next turn to a regression analysis.

We build an unbalanced panel for 32 countries from 1978 to 2016 using data on indexed real industry natural gas prices from the International Energy Agency (IEA). We then estimate the following relationship between the direction of innovation and natural gas prices:

$$\sinh^{-1}\left(y^{g}_{c,t}\right) - \sinh^{-1}\left(y^{f}_{c,t}\right) = \beta_p \ln p_{c,t-2} + \beta_X X_{c,t-2} + \delta_c + \delta_t + \varepsilon_{c,t}.$$

Here $y^{f}_{c,t}$ and $y^{g}_{c,t}$ are respectively the number of fossil-fuel and green patents in the patent office of country c in year t (Appendix A.1 repeats this exercise focusing just on renewable patents). We use the inverse hyperbolic sine transformation, $\sinh^{-1}$ to accommodate zeros in patent counts, so our left-hand side is approximately equal to the log ratio of green to fossil-fuel patents $\ln\left(y^{g}_{c,t}/y^{f}_{c,t}\right)$ when patents counts are positive. The variable $p_{c,t}$ is the real indexed industrial natural gas price, and, in line with previous work such as Aghion et al. (2016) and Popp (2002), we use the two-year lag of this price to accommodate delay in the impact of natural gas prices on innovation incentives. In addition, $X_{c,t}$ is a vector of controls which includes GDP per capita (from the OECD), public R&D expenditures in fossil-fuel energy or green energy (from the IEA) and log energy consumption (from the World Bank), δ_c and δ_t are country- and year- fixed effects, and $\varepsilon_{c,t}$ is an error term. Country-fixed effects capture time-invariant differences across countries in their propensity to innovate in different technologies. Year-fixed effects capture aggregate shocks such as the 2009 recession or global oil prices. The coefficient of interest β_p is thus based on differential within-country variation in natural gas prices above and beyond global shocks and controlling for fluctuations in GDP per capita, energy consumption, and public R&D support.

Table 1 confirms that there is a positive and significant correlation between the ratio of green to fossil-fuel patents and natural gas prices. Columns (1)-(3) consider all patents, while columns (4)-(6) focus on patents by domestic inventors. The coefficients yield elasticities (except for approximation due to the use of $\sinh^{-1}$ instead of log on the left-hand side). Hence, column (6) indicates that a 1% increase in natural gas prices is associated with a relative increase in domestic green patents compared to fossil-fuel patents of 0.246%. This elasticity is close to Popp's (2002) estimate of the effect of energy prices on energy-saving innovations (which is an elasticity of around 0.3).[7]

Two additional issues are worth discussing. First, the results reported in Table 1 should be interpreted as correlations, which could be impacted by various omitted variables, and other factors may have driven the decline in green innovation documented in Figure 2. Changes in public R&D spending do not appear to have contributed to the decline in green innovation as they do not display a similar reversal. The rise of Chinese solar panel production may have also contributed to this reversal, but is unlikely to be its main driver in the United States, because US innovation in wind technologies show the same decline.[8] Nevertheless, other omitted factors, such as the exhaustion of low-hanging innovation opportunities in green technologies, may have played a role (see Popp et al. 2022, for further discussion).

Second, green innovation matters. While learning-by-doing and scale economies in solar panel production have been important, existing evidence points to a central role for green innovations in the large declines in the costs of renewable energy production. For example, in solar panels, it was new technologies that enabled the deployment of larger crystals for

[7]In these regressions, global shocks to natural gas prices are captured by the time fixed effects, and so is the global response of inventors. We show in the Appendix that if time effects are omitted, the relationship between natural gas prices and green patents we estimate in Table 1 becomes stronger.

[8]See Figure A.3 in the Appendix. Moreover, we see a similar reversal in China as well.

Table 1—Innovation and Gas prices

Dependent Variable:	Green - Fossil-Fuel Electricticity Patents					
Inventors:	All			Domestic		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Gas Price Index)	0.21	0.25	0.22	0.23	0.23	0.25
	(0.10)	(0.13)	(0.11)	(0.15)	(0.09)	(0.10)
ln(GDP/capita)	1.16	2.08	2.22	−0.99	2.56	2.89
	(0.37)	(0.54)	(0.58)	(0.21)	(0.76)	(0.87)
ln(Public R&D Fossil)		−0.01	0.00		−0.07	−0.06
		(0.03)	(0.02)		(0.03)	(0.04)
ln(Public R&D Green)		0.06	0.08		0.00	0.01
		(0.04)	(0.06)		(0.09)	(0.09)
ln(Energy consumption)			−0.41			−0.43
			(0.43)			(0.75)
Year fixed effects	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓
R-squared	0.91	0.93	0.94	0.83	0.88	0.88
Observations	923	636	636	887	608	608
Countries	32	29	29	32	29	29

Note: This table presents results of panel regressions of the direction of innovation on gas prices. The direction of innovation is measured as the $\sinh^{-1}$ difference between the number of green patents in a country and the number of fossil-fuel patents. Patents are allocated to a country according to the location of the patent office and dated from the year of first filing. The independent variables are lagged by two periods. Columns (1) to (3) include all patents, Columns (4) to (6) only include patents by domestic inventors (patents are counted fractionally if there are multiple inventors' nationalities). Gas prices are measured as the log of a real gas price index from the IEA. All regressions control for log GDP per capita, country and year fixed effects. Columns (2), (3), (5) and (6) add controls for log public R&D expenditures in green and fossil-fuel technologies. Columns (3) and (6) also control for log energy consumption. Countries are weighed by total green and fossil-fuel patents, and include: AT, AU, BE, CA, CH, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HU, IE, IT, JP, KR, LT, LU, LV, MX, NL, NZ, PL, PT, SE, SI, SK, TR, US. Standard errors are clustered at the country-level.

ingots and allowed the cutting of ingots into thinner wafers (Carvalho, Dechezleprêtre, and Glachant 2017). In fact, around half of patented innovations in solar photovoltaic cells in the United States concern the currently dominant technology and are therefore relevant for these cost reductions. In a recent study, Kavlak, McNerney, and Trancik (2018) estimate that around 60% of the global cost decline in solar panels between 1980 and 2012 can be attributed to public and private R&D. Interestingly, even in the Chinese case, innovations play a major role. For example, about half of the decline in wind turbine prices in China between 1998 and 2012 appears driven by new innovations (Yu, Li, Che, and Zheng 2017). New technological breakthroughs may be even more important for future advances.

Overall, this section shows that innovation in the electricity sector has been sharply redirected away from renewable and green technologies concurrently with the shale gas boom in the United States. We next develop our conceptual framework, which will enable us to model the short-run and long-run implications of this technology redirection.

3 Theory

In this section, we present our conceptual framework, which models the static and dynamic substitution between three different types of energy—coal, natural gas and green. Dynamic substitution results from directed innovation. After describing the basic outlines of the model, we solve for the static equilibrium and explore the short-term impact of a natural gas boom. We then turn to the dynamic equilibrium, where the direction of innovation responds to the natural gas price. We start with an economy in laissez-faire and then characterizes optimal policy. We introduce BAU policies in Section 4.

3.1 Preferences, Production Technology and the Environment

Time is discrete and the economy is populated by a mass 1 of identical households who live for one period and do not make intertemporal decisions. We define social welfare as

$$U_t = \sum_{\tau=t}^{\infty} \frac{1}{(1+\rho)^{\tau-t}} \frac{C_\tau^{1-\vartheta}}{1-\vartheta}, \tag{1}$$

where C_τ is consumption, ρ is the social planner's rate of time preference, and ϑ is the inverse elasticity of intertemporal substitution. Households inelastically supply L units of production labor and one unit of scientist labor used in innovation.

There is a unique final good, produced with the technology

$$Y_t = (1-D(S_t))\left((1-\nu) Y_{Pt}^{\frac{\lambda-1}{\lambda}} + \nu \left(\widetilde{A}_E E_t\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}, \tag{2}$$

where $\nu \in (0,1)$, E_t is an energy composite, Y_{Pt} is a production input, $\widetilde{A}_E$ represents energy efficiency and λ is the elasticity of substitution between energy and the production input. We assume $\lambda \in (0,1)$ so that energy and other inputs are gross complements. There are no savings and the final good is used only for consumption, so that $Y_t = C_t$. The variable S_t is the carbon concentration in the atmosphere and the function $D(S_t)$ represents the environmental damage on production. We adopt Golosov, Hassler, Krusell, and Tsyvinski's (2014) representation and assume that $D(S_t) = 1 - e^{-\zeta(S_t - S_0)}$, where S_0 is the pre-industrial carbon concentration and $\zeta > 0$. The production input is produced according to $Y_{Pt} = A_{Pt} L_{Pt}$ where A_{Pt} is a productivity parameter and L_{Pt} is labor used in the production sector.

The energy composite is generated according to the function

$$E_t = \left(\kappa_c E_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + \kappa_s E_{st}^{\frac{\varepsilon-1}{\varepsilon}} + \kappa_g E_{gt}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{3}$$

where E_{ct}, E_{st}, and E_{gt} respectively denote coal, natural gas, and green energy. In addition, the κ's are share parameters. This specification implies that the three types of energy are substitutes with an elasticity of substitution $\varepsilon > 1$. In Section 4, we allow for different elasticities within fossil fuels and between fossil fuels and green technologies.

Energy production of each type $i \in \{c, s, g\}$ combines an extracted resource R_{it} with fuel-specific energy ("power plant") inputs Q_{it}, with the Leontief production function

$$E_{it} = \min\{Q_{it}, R_{it}\}. \tag{4}$$

The Leontief technology implies that, in equilibrium, $E_{it} = Q_{it} = R_{it}$. The power plant input for each $i \in \{c, s, g\}$ is produced according to a Cobb-Douglas production function,

$$Q_{it} = \exp\left(\int_0^1 \ln q_{ijt}\, dj\right) \tag{5}$$

where q_{ijt} is an intermediate supplied by technology monopolist j for energy type i. We assume that all intermediates are produced linearly using labor:

$$q_{ijt} = A_{ijt} l_{ijt}^q, \tag{6}$$

where l_{ijt}^q denotes the amount of labor hired and A_{ijt} is the productivity of intermediate j for energy type i at time t. Average productivity for energy type i at time t is

$$\ln A_{it} = \int_0^1 \ln A_{ijt}\, dj, \tag{7}$$

and summarizes one dimension of energy technology.

The other dimension pertains to resource extraction. Extraction for green technology is assumed to be free (e.g., from wind or the sun), while extraction is costly for coal and natural gas. We also allow technological change in resource extraction as we explain below. Specifically, extracting one unit of coal or natural gas requires one unit of an extraction input. With a slight abuse of notation, we denote the extraction input for energy type $i \in \{c, s\}$ by

R_{it} (since the amount of resource extracted is equal to this input). We model the production of the extraction input analogously, with a Cobb-Douglas aggregator of intermediates,

$$R_{it} = \exp\left(\int_0^1 \ln r_{ijt} dj\right),$$

where each extraction intermediate r_{ijt} is produced with labor l^r_{ijt} and productivity B_{ijt}: $r_{ijt} = B_{ijt} l^r_{ijt}$. We also define average productivity in extraction for energy type $i \in \{c, s\}$ as

$$\ln B_{it} = \int_0^1 \ln B_{ijt} dj.$$

Finally, we assume that, like renewables, coal and natural gas are in infinite supply.[9]

We denote the carbon intensity of electricity production from coal and gas by, respectively, ξ_c and $\xi_s < \xi_c$. This inequality implies that natural gas is cleaner than coal. Green energy generates zero greenhouse gas emissions, $\xi_g = 0$. We denote emissions from energy type i at date t by $P_{it} = \xi_i R_{it}$. Aggregate emissions are then given by $P_t = \xi_c R_{ct} + \xi_s R_{st}$. Though the exact dynamics of the atmospheric carbon stock S_t are not central to our theoretical results, we adopt the carbon cycle specification of Golosov et al. (2014), so that:

$$S_t = \overline{S} + \sum_{s=0}^{t+T} (\varphi_L + (1-\varphi_L)\varphi_0(1-\varphi_d)^s) P_{t-s}, \tag{8}$$

where $\overline{S}$ is pre-industrial carbon concentration. This formulation reflects that a share φ_L of emissions stay in the atmosphere forever, while out of the remaining emissions, a share $1-\varphi_0$ is immediately absorbed and the rest decays geometrically at the rate φ_d. In the quantitative section, we also incorporate emissions from the rest of the world.

3.2 Innovation and the Direction of Technology

Intermediate productivities, the A_{ijt}'s, increase over time due to innovation, building on the previous best vintage. We assume that innovation uses only scientist labor as input. Scientists that innovate successfully over an intermediate raise that intermediate's productivity by a

[9]Coal reserves that can be recovered with the current technology in the United States are 470 times the current level of consumption, while the "demonstrated reserve base" that can be extracted in the future is twice this amount (EIA 2021). For natural gas, the amount of recoverable resources are about 98 times the current level of consumption (EIA 2022), and reserves of methane hydrates, which could be commercially viable with future technologies, are estimated to be much larger.

factor $\gamma > 1$, so that $A_{ijt} = \gamma A_{ij(t-1)}$ when there is innovation at date t for intermediate j for energy type i. Following such an innovation, the scientist becomes the monopolist supplier of the intermediate. We assume that this monopolist is constrained by the next-best (previous) technology and, in order to exclude entrants, sets a limit price with a gross markup of γ.

Innovation is directed, and in particular, scientists decide to allocate their research efforts between the fossil-fuel energy inputs or the green energy input. This formulation is motivated by the fact that, in practice, many inputs in coal and natural gas power plants are similar and keeping track of only two technologies simplifies the analysis (see Section 5.2 for an extension where innovation is directed between the three sectors). There is potentially congestion in research effort, with different scientists chasing similar new ideas when working in the same field. Consequently, the probability of success of innovation directed at energy type i at time t is $\eta s_{it}^{-\psi}$ per scientist, where s_{it} is the total number of scientists exerting effort towards innovations for this energy type, ψ parameterizes the extent of the congestion effects (diminishing returns), and η represents research productivity. For simplicity, and without any major loss of insight, we assume the same research productivity in both sectors. As a result, the evolution of the average productivity is in the production of the three types of energy can be written as:[10]

$$A_{ct} = \gamma^{\eta s_{ft}^{1-\psi}} A_{c(t-1)}, A_{st} = \gamma^{\eta s_{ft}^{1-\psi}} A_{s(t-1)} \text{ and } A_{gt} = \gamma^{\eta s_{gt}^{1-\psi}} A_{g(t-1)}. \tag{9}$$

As in AABH, we assume that patents only last one period so that scientists maximize profits in the current period (rather than the discounted sum of future profits). This simplification is immaterial given our focus, and Acemoglu et al. (2016) incorporate forward-looking innovation behavior in a similar setup.

Finally, the productivities in extraction, B_{ct} and B_{st}, and in input production, A_{Pt}, evolve exogenously. We outline in Section 5.1 how extraction technologies can be endogenized. To amplify the parallel between the energy inputs and the other inputs, we assume that extraction intermediates and the production input are supplied with the same gross markup as the energy intermediates, $\gamma > 1$. Our main focus is to study the effects of an exogenous improvement in the extraction of natural gas, B_{st}, on emissions and the direction of innovation.

[10] This follows because $\ln A_t - \ln A_{t-1} = \int_0^1 \ln A_{jt} dj - \int_0^1 \ln A_{j(t-1)} dj = \int_0^1 \varepsilon_{jt} dj$, where ε_{jt} is an iid random variable that takes the value zero with probability $1 - \eta s^{1-\psi}$ (no innovation) and $\ln \gamma$ with probability $\eta s_t^{1-\psi}$ (innovation). Appealing to the law of large numbers (and ignoring technical details to do with continuums), this gives $\ln A_t - \ln A_{t-1} = \mathbb{E}[\varepsilon_{jt}] = \eta s_t^{1-\psi} \ln \gamma$. Taking exponents gives equation (9).

3.3 Short-run Effects of a Natural Gas Boom

We first take the productivity of different intermediates, the A_{ijt}'s as given and focus on the static equilibrium. A static equilibrium is defined as an allocation in which all energy types and the final good production sector minimize costs, the intermediate monopolists maximize profits, and all markets clear. It is straightforward to verify that a static equilibrium always exists and is unique, and we now characterize it.

For notational simplicity, we drop the subscript t in this subsection. We take the final good to be the numeraire throughout, and let p_i^q denote the price of the energy input and p_i^r the price of the resource extraction input ($p_g^r = 0$ since extraction is free in green technologies). With Cobb-Douglas production and Bertrand competition from the next-best technology, the equilibrium price of the energy intermediate ij is equal to $p_{ij}^q = \gamma w / A_{ij}$. Aggregating across intermediates, the price of the energy input i is

$$p_i^q = \frac{\gamma w}{A_i}. \tag{10}$$

The resulting profits for intermediate ij are

$$\pi_{ij}^q \equiv \left(1 - \frac{1}{\gamma}\right) p_i^q Q_i. \tag{11}$$

Under our assumption that there is also a gross markup equal to γ for extraction intermediates, we obtain the price of extracted resource input as $p_i^r = \gamma w / B_i$.

Next, the Leontief technology imposes that the equilibrium price of electricity of type i will be equal to the cost of the power plant and extraction inputs, and thus

$$p_i = p_i^q + p_i^r = \frac{\gamma w}{C_i} \text{ with } \frac{1}{C_i} \equiv \frac{1}{A_i} + \frac{1}{B_i}, \tag{12}$$

where C_i, the harmonic mean of A_i and B_i, gives the overall productivity in the production of electricity of type $i \in \{c, s, g\}$. For each energy type i, cost-minimization implies

$$E_i = \kappa_i^\varepsilon \left(\frac{C_i}{C_E}\right)^\varepsilon E \text{ with } C_E \equiv \left(\kappa_c^\varepsilon C_c^{\varepsilon-1} + \kappa_s^\varepsilon C_s^{\varepsilon-1} + \kappa_g^\varepsilon C_g^{\varepsilon-1}\right)^{\frac{1}{\varepsilon-1}}. \tag{13}$$

C_E is the overall productivity of the energy sector. The equilibrium price of the energy composite and the equilibrium level of production are then

$$p_E = \frac{\gamma w}{C_E} \text{ and } E = C_E L_E, \tag{14}$$

where L_E is total labor hired by the energy sector.[11] The relative sizes of the energy subsectors depend on their relative productivities and are given by

$$\Theta_i = \frac{p_i E_i}{p_E E} = \kappa_i^{\varepsilon} \left(\frac{C_i}{C_E} \right)^{\varepsilon - 1}.$$

The equilibrium level of pollution can be computed as

$$P = \xi_E E \text{ with } \xi_E \equiv \xi_c \kappa_c^{\varepsilon} \left(\frac{C_c}{C_E} \right)^{\varepsilon} + \xi_s \kappa_s^{\varepsilon} \left(\frac{C_s}{C_E} \right)^{\varepsilon}, \tag{16}$$

where ξ_E measures the average emission intensity of energy production.

We now consider the implications of a natural gas boom, driven by an increase in the productivity of extraction for gas, B_s, on total emissions, P..

The static impact of the natural gas boom on emissions can be decomposed into a substitution and a scale effect:

$$\frac{\partial \ln P}{\partial \ln B_s} = \underbrace{\frac{\partial \ln \xi_E}{\partial \ln B_s}}_{\text{substitution effect}} + \underbrace{\frac{\partial \ln E}{\partial \ln B_s}}_{\text{scale effect}}. \tag{17}$$

The substitution effect is rooted in the changes in the average pollution intensity of energy resulting from the natural gas boom, while the scale effect is driven by the expansion of energy due to the sector's higher average productivity. The scale effect is closely related to, but different from Jevons' paradox, which results when the efficiency of a resource increases, raising its overall use. Here, the natural gas boom does not directly increase resource efficiency, but it improves the average productivity of the energy sector.

Due to the intermediate emission intensity of natural gas, the substitution effect has an

[11] The allocation of labor follows from cost-minimization in the final good sector. Taking the ratio of the first-order conditions with respect to E and L_P, and using labor market clearing, we get

$$L_E = \frac{\nu^{\lambda} \widetilde{A}_E^{\lambda-1} C_E^{\lambda-1}}{\nu^{\lambda} \widetilde{A}_E^{\lambda-1} C_E^{\lambda-1} + (1-\nu)^{\lambda} A_P^{\lambda-1}} L. \tag{15}$$

Labor in the energy sector decreases with average productivity C_E, because energy and production inputs are gross complements ($\lambda < 1$).

ambiguous sign: negative when natural gas mostly replaces coal, but positive when it mostly replaces green energy. Mathematically, we can express this substitution effect as

$$\frac{\partial \ln \xi_E}{\partial \ln B_s} = \varepsilon \frac{\partial \ln C_s}{\partial \ln B_s} \left(\frac{P_s}{P} - \Theta_s \right), \tag{18}$$

where recall that Θ_s is the revenue share of natural gas in the energy sector, while $P_s/P = \xi_c \kappa_c^\varepsilon C_c^\varepsilon / \left(\xi_c \kappa_c^\varepsilon C_c^\varepsilon + \xi_s \kappa_s^\varepsilon C_s^\varepsilon \right)$ is its emissions share. In addition, $\partial \ln C_s / \partial \ln B_s = C_s / B_s > 0$ represents the effect of an increase of the extraction technology on the average productivity of natural gas energy. This expression clarifies that the substitution effect will be negative, and natural gas will reduce emissions at given scale, when the pollution share of natural gas is lower than its energy share: $P_s/P < \Theta_s$. This condition is satisfied when the the emission intensity of natural gas, ξ_s, is relatively low or when the revenue share of green energy, Θ_g, is small – in that case Θ_s is always greater than P_s/P since $\xi_s < \xi_c$.

The scale effect term, on the other hand, is always positive and equal to

$$\frac{\partial \ln E}{\partial \ln B_s} = \frac{C_s}{B_s} \Theta_s \left(\lambda + (1-\lambda) \Omega_E \right),$$

where $\Omega_E \equiv p_E E / Y$ is the revenue share of energy in the economy. The scale effect is larger when less labor gets reallocated from the energy sector to the production sector, which occurs when the elasticity λ and the energy revenue share (Ω_E) are larger.

Thus the overall impact of a natural gas boom on pollution is given by

$$\frac{\partial \ln P}{\partial \ln B_s} = \frac{C_s}{B_s} \left(\varepsilon \left(\frac{P_s}{P} - \Theta_s \right) + \Theta_s \left(\lambda + (1-\lambda) \Omega_E \right) \right).$$

Since $\varepsilon > 1$ and $\lambda < 1$, a negative substitution effect may dominate the scale effect and in fact does so provided that natural gas is sufficiently clean relative to coal.[12] This establishes the main result of the static analysis:

Proposition 1 *A natural gas boom (a one time increase in B_s) leads to a decrease in emissions in the short-run provided that natural gas is sufficiently clean compared to coal (that is, provided*

[12] Substituting for P_s/P, Θ_s and Ω_E, we have that $\partial \ln P / \partial \ln B_s < 0$ if and only if

$$\frac{\xi_s}{\xi_c} < \frac{\kappa_c^\varepsilon C_c^\varepsilon \left[\varepsilon - \left(\lambda + (1-\lambda) \frac{\nu^\lambda \widetilde{A}_{Et}^{\lambda-1} C_E^{\lambda-1}}{\nu^\lambda \widetilde{A}_{Et}^{\lambda-1} C_E^{\lambda-1} + (1-\nu)^{\lambda-1} A_P^{\lambda-1}} \right) \right]}{\left[\kappa_s^\varepsilon C_s^\varepsilon \left(\lambda + (1-\lambda) \frac{\nu^\lambda \widetilde{A}_{Et}^{\lambda-1} C_E^{\lambda-1}}{\nu^\lambda \widetilde{A}_{Et}^{\lambda-1} C_E^{\lambda-1} + (1-\nu)^{\lambda-1} A_P^{\lambda-1}} \right) + \varepsilon C_s \left(\kappa_c^\varepsilon C_c^{\varepsilon-1} + \kappa_g^\varepsilon C_g^{\varepsilon-1} \right) \right]}.$$

that ξ_s/ξ_c is sufficiently small).

3.4 Directed Innovation and the Dynamic Equilibrium

A dynamic equilibrium is a sequence of static equilibria with the vector of productivities for power plant inputs, the A_{ijt}'s, evolving according to the equilibrium allocation of scientists and the productivities for extraction inputs, B_{ct} and B_{st}, and the production input A_{Pt} evolving exogenously. The allocation of scientists is determined by an innovation equilibrium condition, requiring that they expect the same returns from devoting effort to fossil-fuel and green innovations.[13] These returns are the static profits, (11), multiplied by the probability of success. Thus, the expected returns from innovation in green energy are

$$\Pi_{gt} = \eta s_{gt}^{-\psi}\left(1-\frac{1}{\gamma}\right)p_{gt}E_{gt}. \tag{19}$$

Similarly, the expected profits of devoting innovation efforts to fossil fuel are

$$\Pi_{ft} = \eta s_{ft}^{-\psi}\left(1-\frac{1}{\gamma}\right)\left(p_{ct}^{q}Q_{ct}+p_{st}^{q}Q_{st}\right) = \eta s_{ft}^{-\psi}\left(1-\frac{1}{\gamma}\right)\left(\frac{C_{ct}}{A_{ct}}p_{ct}E_{ct}+\frac{C_{st}}{A_{st}}p_{st}E_{st}\right). \tag{20}$$

This last expression incorporates the fact that fossil-fuel innovations are used both by coal and natural gas inputs. Notice also that power plant inputs for energy type i only receive a share C_i/A_i of the revenues generated by this type of energy, with the remainder accruing to the extraction input because of the Leontief technology. Since innovation only responds to current profits, the discount rate, ρ, does not matter for the dynamic equilibrium allocation.

Hence, the innovation equilibrium condition can be written as

$$\frac{\Pi_{gt}}{\Pi_{ft}} = \frac{s_{gt}^{-\psi}\kappa_g^{\varepsilon}C_{gt}^{\varepsilon-1}}{s_{ft}^{-\psi}\left(\kappa_c^{\varepsilon}\frac{C_{ct}^{\varepsilon}}{A_{ct}}+\kappa_s^{\varepsilon}\frac{C_{st}^{\varepsilon}}{A_{st}}\right)} = 1. \tag{21}$$

We show in Appendix A that this condition uniquely determines the allocation of innovation effort in equilibrium provided that the following assumption is satisfied:

Assumption 1 $\eta\ln\gamma < \psi/((\varepsilon-1)(1-\psi))$.

We thus have:

[13] Since $\psi > 0$, for any finite t, there cannot be a corner equilibrium in which all scientists work on one type of technology. But asymptotically, the economy can converge to an equilibrium in which all innovation is in one of the two technologies.

Proposition 2 *Under Assumption 1, a dynamic equilibrium exists and is unique.*

Moreover, we can also derive an approximate explicit expression for relative research effort devoted to green innovations. Specifically, when the maximal achievable growth rate $\eta \ln(\gamma)$ is sufficiently small, we have:

$$\left(\frac{s_{gt}}{s_{ft}}\right)^{\psi} \approx \frac{\kappa_g^{\varepsilon} C_{g(t-1)}^{\varepsilon-1}}{\frac{1}{A_{c(t-1)}}\kappa_c^{\varepsilon}\left(\frac{1}{A_{c(t-1)}}+\frac{1}{B_{ct}}\right)^{-\varepsilon}+\frac{1}{A_{s(t-1)}}\kappa_d^{\varepsilon}\left(\frac{1}{A_{s(t-1)}}+\frac{1}{B_{st}}\right)^{-\varepsilon}}. \tag{22}$$

This expression highlights that, as in AABH, the direction of technology in the energy sector features path dependence: higher green productivity at time $t-1$, $A_{g(t-1)}(=C_{g(t-1)})$ increases the relative size of the green energy sector, which then favors further green innovations at time t. Similarly, higher productivity levels, $A_{c(t-1)}$ and $A_{s(t-1)}$, increase the relative size of the fossil-fuel sector, a force which encourages further fossil-fuel innovations.

A new element in (22) is the role of productivity in the extraction sector. When productivity in fossil-fuel power plant technologies, $A_{c(t-1)}$ and $A_{s(t-1)}$, are high relative to productivity in extraction, B_{ct} and B_{st}, fossil-fuel innovations are discouraged, as a higher share of revenues from fossil-fuel energy goes to extraction, leaving less incentives for further innovations for power plant inputs. As a result, an increase in $A_{c(t-1)}$ or $A_{s(t-1)}$ has generally an ambiguous effect on the direction of innovation. This effect highlights the important role that the evolution of extraction productivity plays in the direction of innovation.

This discussion also starts building an intuition regarding the impact of a natural gas boom on the direction of technology in the energy sector. Since the right-hand side of (22) is decreasing in B_{st}, a higher B_{st} encourages further fossil-fuel innovations and discourages green innovations. Intuitively, cheaper natural gas both increases the size of the fossil-fuel sector and raises the demand for the complementary power plant inputs at given sector size.

In sum, a natural gas boom at time 1 (an increase in B_{st} for $t \geq 1$) reduces current innovation in green technologies (i.e., s_{g1} decreases). This leads to higher levels of A_{c1} and A_{s1} and a lower level for the green technology A_{g1}.

The full effects of the natural gas boom over time are more complex, however. On the one hand, an increase in the productivity of power plant inputs further encourages fossil-fuel innovations via path dependence, so that the negative effect of the boom on green innovation builds on itself over time. On the other hand, the same impulse also creates counteracting effects if extraction technologies are too far behind. In what follows, we simplify the discussion by imposing the assumption that $\min\left\{B_{ct}/A_{c(t-1)}, B_{st}/A_{s(t-1)}\right\} > \gamma^{\eta}/(\varepsilon-1)$, which ensures that this counteracting effect is dominated. This is a sufficient, but not necessary condition, that enables us to provide the following simple characterization of the dynamic implications of a natural gas boom.

Proposition 3 *Under Assumption 1, a natural gas boom (an increase in B_{st} for all $t \geq 1$) reduces s_{g1} and depresses innovation in green technologies. Moreover, if $\min\{B_{ct}/A_{c(t-1)}, B_{st}/A_{s(t-1)}\} > \gamma^{\eta}/(\varepsilon-1)$ for all $t > 1$, then green innovation declines for all $t \geq 1$.*

This proposition provides sufficient conditions under which a natural gas boom leads to a permanent reallocation of innovation effort away from green technologies. The overall climate impact of a natural gas boom will be determined by a balance between its short-run effects (which are beneficial under the conditions of Proposition 1) and its potential negative long-run effects via reduced green innovations, as we study next.

3.5 Long-run Emission Consequences of a Natural Gas Boom

To fully characterize the effect of the natural gas boom on emissions, consumption and welfare, we need to specify the growth processes for the extraction and the production input technologies. With this aim, we suppose that A_{Pt} grows at the rate $\gamma^{\eta}-1$ and that the extraction technologies B_{ct} and B_{st} grow at the rate $\gamma^{\eta_B}-1$, with $\eta_B \in [0,\eta]$. We then say that the economy is on a *green path*, if, asymptotically, innovation only occurs in green technologies. Conversely, we say that the economy is on a *fossil-fuel path*, if, asymptotically, innovation only occurs in fossil-fuel technologies. Note that output gross of climate damages (without the $D(S_t)$ term) grows asymptotically at the rate $\gamma^{\eta}-1$ if the economy is on a green path, and at the rate $\gamma^{\eta_B}-1$ if it is on a fossil-fuel path.

In this section, we simplify the discussion by focusing on the case where extraction technologies grow at a sufficiently fast rate, that is η_B is above some threshold $\overline{\eta}$.[14] This assumption has two important consequences. First, because in this case extraction technologies are not a limiting factor, the allocation of innovation is asymptotically "bang-bang" as in AABH, with either all scientists working on green innovation or on fossil fuels (except for a knife-edge case). More specifically, there exists a threshold value $\overline{A}_{g0}(A_{s0}, A_{c0}, B_{s1}, B_{c1})$, which depends on the initial productivities in fossil-fuel technologies,

[14] Notice that $\overline{\eta} < \eta$ and we derive an explicit expressions for $\overline{\eta}$ in Appendix A.4.

such that if initially, productivity in the green technology lies below this threshold (that is, if $A_{g0} < \overline{A}_{g0}$), then the economy is on a fossil-fuel path. The opposite occurs and the economy is on a green path if the initial green technology is above this threshold, that is, if $A_{g0} > \overline{A}_{g0}$. Second, we can characterize conditions under which if the inequality $\min\left\{B_{ct}/A_{c(t-1)}, B_{st}/A_{s(t-1)}\right\} > \gamma^{\eta_f}/(\varepsilon-1)$ holds for $t=1$, then it holds for all t. In that case, Proposition 3 implies that the natural gas boom permanently reallocates research inputs away from green technologies.[15]

The next proposition establishes the long-run consequences of a natural gas boom on emissions and characterizes conditions under which it can shift the economy from a green to a fossil-fuel path (proof in Appendix A.4).

Proposition 4 *Suppose Assumption 1 holds,* $\min\{B_{c1}/A_{c0}, B_{s1}/A_{s0}\} > \gamma^{\eta}/(\varepsilon-1)$ *and* B_{ct} *and* B_{st} *grow exogenously at the rate* $\gamma^{\eta_B}-1$ *with* $\eta_B > \overline{\eta}$*. Then, there exist thresholds for initial green energy productivity,* $\underline{A_{g0}}$ *and* $\overline{A_{g0}} > \underline{A_{g0}}$*, such that:*

1. When $A_{g0} \in \left(\underline{A_{g0}}, \overline{A_{g0}}\right)$*, the shale gas boom decreases green innovation permanently. Asymptotically, all innovation takes place in fossil-fuel technologies following a natural gas boom at time* $t=1$*, but all innovation would have been in green technologies without the boom. Long-run emissions grow asymptotically at the rate* $\gamma^{\eta_B}-1$ *with the boom but converge to zero without the boom.*

2. When $A_{g0} < \underline{A_{g0}}$*, asymptotically all innovation is in fossil-fuel technologies with or without the boom. Emissions grow asymptotically at the rate* $\gamma^{\eta_B}-1$ *with or without the boom.*

3. When $A_{g0} > \overline{A_{g0}}$*, asymptotically all innovation is in green technologies with or without the boom but the boom permanently decreases green innovation. Long-run emissions converge to zero with or without the boom, but there exists a* $\overline{t}$ *such that for* $t > \overline{t}$*, emissions are larger with the boom than without.*

Proposition 4 contains two of the most important results of our analysis. First, the natural gas boom generally leads to a permanent decline in green innovation and greater long-run emissions (provided that we are not already on a fossil-fuel path).[16] Second, the natural

[15] For η_B sufficiently small, the condition $\min\left\{B_{ct}/A_{c(t-1)}, B_{st}/A_{s(t-1)}\right\} > \gamma^{\eta_f}/(\varepsilon-1)$ cannot be satisfied at all times and the economy cannot converge toward a fossil-fuel path in the long-run. We study this case in Section 5.1. We derive conditions under which the natural gas boom still delays the transition toward green innovation. Appendix A.3 characterizes the long-run behavior of the economy for any value of η_B.

[16] Technically, we can prove that the boom decreases green innovation when $A_{g0} > \underline{A}_{g0}$. When $A_{g0} < \underline{A}_{g0}$, we can also prove this as long as long as fossil-fuel innovations are not too high to start with, that is for $s_{ft} \leq (\eta_B/\eta)^{1/(1-\psi)}$, but even this condition is not necessary.

gas boom increases the threshold value $\overline{A}_{g0}$, such that, for intermediate values of the initial green productivity A_{g0}, we can have the following "fossil-fuel trap" configuration (part 1): without the natural gas boom, the economy was on a green innovation path, but after the natural gas boom it is pushed into the fossil-fuel path. Implications for long-run emissions and output are striking. While on a green innovation path emissions asymptotically converge to zero, they keep growing along the fossil-fuel path. As a result, output grows at a positive rate in the long-run on the green path, but it converges to zero on the fossil-fuel path as the term $D(S_t)$ in (2) converges to one.

We next discuss the welfare effects of the natural gas boom and optimal policy, and then in the next section turn to a quantitative analysis of these effects, where one of our key questions will be whether the US economy is near the intermediate values for the productivity of the green technology that leads to a fossil-fuel trap.

3.6 Welfare and Optimal Policy

Proposition 4 shows how a natural gas boom increases long-run emissions. But counter-balancing this, such a boom reduces short-run emissions (provided that the conditions in Proposition 1 are satisfied) and short-run output always increases. The next proposition explores the implications of these two opposing forces on welfare (proof in Appendix A.5).

Proposition 5 *Suppose Assumption 1 holds,* $\min\{B_{c1}/A_{c0}, B_{s1}/A_{s0}\} > \gamma^{\eta}/(\varepsilon - 1)$*,* B_{ct} *and* B_{st} *grow exogenously at the rate* $\gamma^{\eta_B} - 1$ *with* $\eta_B > \overline{\eta}$ *and* $A_{g0} \in \left(\underline{A_{g0}}, \overline{A_{g0}}\right)$*. Then the natural gas boom reduces social welfare if the discount rate* ρ *is less than some threshold* $\overline{\rho}$ *(where* $\overline{\rho} > 0$*) or if the inverse elasticity of intertemporal substitution* ϑ *is greater than* 1.

To understand this result, first note that, in our model, a natural gas boom creates short-run benefits and long-run costs. Hence, the finding that the costs will exceed the benefits for sufficiently small discount rates is intuitive.

To gain additional intuition, let us consider the three cases in Proposition 4 separately. When $A_{g0} \in \left(\underline{A_{g0}}, \overline{A_{g0}}\right)$, the natural gas boom shifts the economy from a green path to a fossil-fuel path, with dramatic effects on long-run emissions and thus on output (inclusive of environmental damages captured by the term $D(S_t)$ in (2)). In particular, output net of climate damages grows at the rate $\gamma^{\eta} - 1$ without the boom but converges to 0 with the boom (which is in line with the exponential net-of-damage function adopted in Golosov et al., 2014). The resulting very low levels of utility in the future matter more when ρ is low. Moreover, when ϑ is above 1, the flow utility tends to $-\infty$.[17]

When $A_{g0} > \overline{A_{g0}}$, the natural gas boom raises emissions in the long-run, but the economy still remains on the green path and long-run emissions still converge to zero. Nevertheless, even in this case, such a boom can reduce welfare, because by reducing green innovation, it depresses long-run output (since long-run energy is entirely met by clean technologies in the green path). This reduces welfare provided that the future matters sufficiently—meaning that the interest rate minus the growth rate is sufficiently low. Recall that $r-g$ being small is equivalent to $\frac{\gamma^{\eta(1-\vartheta)}}{1+\rho}$ being large, since $r \approx \rho + \vartheta g$ and $g \approx \eta \ln \gamma$. Hence, low levels of ρ again make the negative welfare effects more likely.[18]

Finally, when $A_{g0} < \underline{A_{g0}}$, long-run net output becomes very low in the long-run since emissions grow exponentially. This leads to a very low welfare, with or without the boom, and even more so when ρ is small and ϑ is large.

We next determine how optimal policy should respond to a natural gas boom. As in AABH, there are two inefficiencies in this economy: the environmental externality (due to the fact that fossil-fuel technologies lead to carbon emissions) and innovation distortions (because scientists do not fully appropriate the returns from the technologies they invent).[19] Optimal policy has to deal with both margins of inefficiency leading to the next proposition (the proof is straightforward and is presented in Supplementary Appendix B.1.3):

Proposition 6 *1. Optimal policy can be implemented by a carbon tax and a subsidy to green innovation (financed or reversed lump-sum).*

2. Under the optimal policy, a natural gas boom always increases welfare.

As in AABH, the optimal carbon tax is given by the standard Pigovian formula and corrects for the environmental externality.[20] The research subsidy, on the other hand, is intended to correct the distorted allocation of scientists between fossil-fuel and green innovations. The

[17]More specifically, we can show that when $\vartheta > 1$, flow utility limits to $-\infty$ sufficiently fast, as carbon concentration in the atmosphere increases. Therefore, the welfare effects of the natural gas boom are negative for any discount rate in this case.

[18]In this case, negative welfare effects are also more likely when carbon concentrations depend more on current emissions than the existing stock of carbon—i.e., when φ_L is small and φ_D is large.

[19]Since all sectors share the same monopolistic structure and the final good is not used for production, there is no monopoly distortion in the final good production.

[20]If we assume log preferences ($\vartheta = 1$) as in Golosov et al. (2014), then we obtain the same closed-form solution for the carbon tax, $\tau_t = Y_t \zeta (1+\rho)\left(\frac{\varphi_L}{\rho} + \frac{(1-\varphi_L)\varphi_0}{\rho+\varphi_d}\right)$. In addition, it is straightforward to establish that if $\vartheta > 1$ or if $\rho < \bar{\rho}$, then optimal policy always induces a green path.

laissez-faire allocation of research effort is distorted because scientists do not capture the full social value of their innovation. The optimal allocation of scientists can be computed as

$$\left(\frac{s_{ft}}{s_{gt}}\right)^{\psi} = \frac{\sum_{u=0}^{\infty} \frac{1}{1+r_{t,t+u}} \left(\frac{C_{c(t+u)}}{A_{c(t+u)}} p_{c(t+u)} E_{c(t+u)} + \frac{C_{s(t+u)}}{A_{s(t+u)}} p_{s(t+u)} E_{s(t+u)}\right)}{\sum_{u=0}^{\infty} \frac{1}{1+r_{t,t+u}} p_{g(t+u)} E_{g(t+u)}},$$

where $r_{t,t+u}$ is the (shadow) interest rate between t and $t+u$, given by $1+r_{t,t+u} = (1+\rho)^{u} C_{t+u}^{\vartheta} / C_{t}^{\vartheta}$. The right-hand side of this expression corresponds to the ratio between the discounted sum of benefits from innovations in fossil-fuel and green technologies. Notice that the (social) benefits from innovation are proportional to the revenues of the sectors and, in the case of fossil-fuel technologies, they are also adjusted for the share of revenues going to extraction rather than power plants (which is what the the ratio of $C_{i(t+u)}/A_{i(t+u)}$ achieves). Compared to this, the laissez-faire equilibrium only features expected profits in the current period on the right-hand side, accounting for the divergence between the optimum and the equilibrium, which optimal policy corrects for. Optimal policy typically involves a clean innovation subsidy because it induces a transition toward green technology and consequently, there will be more clean innovation in the future to benefit from the knowledge created by current clean innovation— compared to fossil-fuel innovations. The clean innovation subsidy internalizes this future social benefit.[21]

This formula also provides an intuition for why a natural gas boom generally necessitates higher subsidies to green innovation. While contemporaneous private returns from innovation shift in favor of fossil-fuel technologies after a natural gas boom, long-run relative social values of fossil-fuel and green innovations do not change as much (provided that the social planner still prefers a green path). Consequently, more aggressive subsidies to green innovation are needed to align social and private returns.

The second part of the proposition is intuitive as well. A natural gas boom improves the production possibilities frontier of the economy. If the social planner can induce the optimal allocation, then she will always improve welfare.

Finally, we note that the results in Proposition 6 do not depend on the simplifying assumption that innovators only capture current profits. With long-lasting patents, similar

[21]This argument also clarifies that the clean innovation subsidy could be negative if green technologies were expected to become less important in the future. In this case, it would be the current fossil-fuel innovations upon which others will build in the future. This dynamic nature of the externality is also the reason why in a balanced growth path with only one type innovation, there is no need for an innovation subsidy, particularly since the supply of scientists is inelastic.

results apply because future innovators still build on current innovations and current innovators cannot capture all of this benefit, as shown in Acemoglu et al. (2016), Greaker, Heggedal, and Rosendahl (2018), and Hémous and Olsen (2021).

4 Quantitative Model

We now use our model as the basis for a quantitative evaluation of the implications of the US shale gas boom. For the quantitative analysis we add several elements to the model, including "business as usual" (BAU) policies, such as taxes and subsidies for electricity generation, innovation, and mandated local pollution abatement expenditures. The details of parameter choices are presented in Section 4.1. We then present estimates of the short-run implications of the boom in Section 4.2 and its long-run implications in Section 4.3. Section 4.4 presents our results for optimal climate policy. Finally, Section 4.5 discusses welfare effects.

4.1 Calibration and Parameter Choices

A model period corresponds to five years. The pre-boom base period, to which we calibrate the initial equilibrium of the model, covers the years 2006-10. As is standard in the macro-climate literature, we consider an economy with a 400-year horizon.[22]

Electricity and Final Goods Production: We now describe the calibration of electricity and final goods production. To begin, we construct measures of electricity generation costs which now explicitly model costs of mandated expenditures on local pollution abatement (e.g., sulfur dioxide). Letting $\overline{\Lambda_i}$ denote the fraction of the intermediate inputs devoted to local pollution abatement, the equilibrium price of energy type j (gross of generation taxes which are described further below) now satisfies (see Appendix A.7.1):

$$p_i = p_i^q \left(1 + \overline{\Lambda_i}\right) + p_i^r, \tag{23}$$

where p_i^q is the price of the energy input ($p_i^q = \gamma w / A_i$) and p_i^r is again the resource price. Naturally, with this modification, all of our previous results apply replacing A_i by $A_i / \left(1 + \overline{\Lambda_i}\right)$.

To quantify electricity generation costs (p_i) and their components (p_i^q, $p_i^q \overline{\Lambda_i}$ and p_i^r) by energy type, we collect plant- and generator-level data on electricity generation, fuel inputs

[22] E.g., Cai and Lontzek (2019) consider 600 years, Barrage and Nordhaus (2023) consider 400 years, etc.

and costs, operation and management (O&M) expenditures, plant capital, and abatement expenditures as outlined in Table 2.

Table 2—Data Sources for Costs of Electricity Generation

Item	Data Source(s)
Intermediate costs/MWh $p^q_{it}(1+\overline{\Lambda_i})$ (Plant O&M expenditures, capital, output)	Federal Energy Regulatory Commission (FERC) Form 1
Abatement costs/MWh $p^q_{it}\overline{\Lambda_i}$ (Local abatement investment, O&M, output)	Energy Information Administration (EIA) Form 767, Form 923
Fuel resource costs/MWh p^r_{it}	FERC; EIA Form 423, EIA Form 923

Appendix Section A.7.3 presents further details on how we use these data. Before proceeding, we note that the FERC data only covers investor-owned utilities meeting certain generation thresholds. Consequently, the "green" energy generators represented in FERC tilt towards existing nuclear power plants. In order to improve our measure of green generation costs, we also consult levelized cost estimates (LCOE) from Lazard to compute the generation-weighted average capital-labor cost for green technologies in our base period.[23]

A final component of short-run electricity generation costs are the BAU taxes. In our framework, generation taxes and subsidies are modeled as ad-valorem levies τ_{it} imposed on energy type i in period t. For clean energy sources, we quantify BAU policy in each period based on Lazard estimates of differences in the levelized costs of clean energy with and without prevailing federal US investment and production subsidies in each year.[24] The generation-weighted average has been around a 3-4% subsidy until the current period. While the 2020-2024 period is still ongoing and any estimates of its policies are thus inevitably preliminary, we also consider a stylized Inflation Reduction Act quantification that adds the most recent Lazard data along with estimates from Bistline et al. (2023) on the effective subsidy rate for nuclear generation, which suggest a much larger post-IRA effective green generation subsidy of around 20% (in line also with Casey et al. (2023)).[25]

For BAU generation taxes on fossil electricity above and beyond local pollution regulations, we consult OECD estimates of the net effective carbon rate for US electricity generation,

[23]We compute the generation-weighted average LCOE (without subsidies) for green energy for all available years in the base period (2008, 2009, and 2010). We then average FERC and Lazard estimates for green generation costs. Hydroelectricity generation is excluded from these calculations in light of limited projected expansion potential (see e.g., EIA 2019).

[24]Lazard generally presents ranges of LCOE estimates. We use averages between the bounds.

[25]IRA subsidies differ depending on whether producers meet domestic content and labor requirements. We use estimates that assume these conditions are met albeit at a cost to producers.

which has remained as low as \$0.50/tCO2 by 2018 and \$1.03/tCO2 by 2021 (\$2010).[26] We thus assume no carbon-based emissions taxes in the base period (2006-10) and convert these carbon prices into the corresponding ad-valorem rates based on the relevant emissions intensities and adjusted (post-boom) prices. We further assume a doubling of carbon prices in 2020-2024 to reflect increases in both explicit carbon prices such as those observed in California's Cap-and-Trade program and in broader adoption of non-price regulations such as renewable portfolio standards (Greenstone and Nath 2021).

Next, we set the elasticity of substitution between fuels, ε, to 1.8561 based on recent empirical estimates for green and fossil electricity from Papageorgiou, Saam, and Schulte (2017), and the elasticity of substitution between electricity and the production input, λ, to 0.4 in line with estimates of both energy-capital labor elasticities (e.g., Van der Werf 2008) and electricity-other energy elasticities (e.g., Bosetti, Massetti, and Tavoni 2007, see Appendix A.7.4 for further discussion).[27] We set $\nu = 0.5$ without loss of generality since different values of ν can be accommodated by adjusting the level of $\widetilde{A_{E,0}}$.

Table 3—Base Year Energy Production and Prices

	Production $E_{i,0}$ (tril. kWh)	Total price $p_{i,0}$ (\$/MWh)	Resource price $p^r_{i,0}$ (\$/MWh)	Local pollutant abatement cost $\overline{\Lambda_i}$ (avg., %)
Coal	9.5	37.7	21.8	9.6%
Gas	4.1	77.9	61.5	0.5%
Green	4.4	73.3	-	-

Note: This table reports total electricity production decomposed by source for the period 2006-2010, which we compute using micro-data. The table also reports the average cost (in \$2010) of production for each source decomposed between resource costs, local pollution abatement costs and other costs. Data source: FERC, Lazard and authors' computation.

Using our estimates of generation costs, BAU policies, the substitution elasticity, and data on electricity consumption in Table 3, we can now solve for the κ's to match relative input demands in the electricity sector imposing $1 = \kappa_c + \kappa_s + \kappa_g$ (see Appendix A.7.2):

$$\frac{E_{c,t}}{E_{s,t}} = \left(\frac{\kappa_c}{\kappa_s}\frac{(1+\tau_{st})p_{st}}{(1+\tau_{ct})p_{ct}}\right)^{\varepsilon} \text{ and } \frac{E_{g,t}}{E_{s,t}} = \left(\frac{\kappa_g}{\kappa_s}\frac{(1+\tau_{st})p_{st}}{\left(1+\tau_{gt}\right)p_{gt}}\right)^{\varepsilon} \tag{24}$$

These estimates then yield the initial electricity composite quantity E_0, price p_{E0} and energy

[26] Intuitively, these low numbers reflect the facts that salient carbon pricing initiatives such as the California Cap-and-Trade program or the Eastern U.S. Regional Greenhouse Gas Emissions Initiative cover only a minority of US emissions and have imposed only modest prices for most of their existence.

[27] We consider different substitution elasticities between gas and renewables and between gas and coal in the extended quantitative model in Section 5.2. Using annual data on 26 countries, Papageorgiou et al. (2017) estimate a CES production function for electricity (the output) that uses fossil fuel and green capacities as inputs. This fits our model well, since we focus on the production of inputs for fossil fuel and green electricity.

efficiency parameter $\widetilde{A_{E0}}$ (see Appendix A.7.4).

Beyond the base period, we assume that energy composite efficiency $\widetilde{A}_{Et}$ is constant, and that the productivity of the general production input A_{Pt} grows at 2% per year. These assumptions, together with our quantification of the innovation process and of the carbon emissions from the rest of the world described below, guarantee that, along the green path, the long-run growth rate of the economy is 2% per year.

To quantify the future productivity of coal and gas extraction (B_{st} and B_{ct}), we obtain Bureau of Labor Statistics estimates of labor productivity in coal mining (NAICS 2121) and oil and gas extraction (NAICS 2111) for all available years until the shale gas boom (1987-2010). The base period generation-weighted average annual extraction productivity growth rate was 1.58%. With slower productivity growth in extraction than in the rest of the economy, the price of fossil-fuel resources increases over time. We use this quantification for η_B as a benchmark, but also consider an alternative scenario with a lower η_B.

Next, we calibrate the innovation step size $\gamma = 1.07$ based on profit data from the US Census Bureau (*Quarterly Financial Reports*) to match that profits are a share $1 - 1/\gamma$ of sectoral income (see Appendix A.7.4 for details).

Given these values, we set the remaining 12 initial equilibrium parameters and unknown variables ($A_{g0}, A_{c0}, A_{s0}, B_{c0}, B_{s0}, C_{c0}, C_{s0}, C_{E0}, A_{P0}, L_{E0}, L_{P0}, w_0$) by solving the system of equations implied by the equilibrium conditions of the model (given in Appendix A.7.4). We then set pollution intensities ξ_c and ξ_s based on the benchmark pollution intensity of each type of electricity generation (EIA, 2016).[28]

Innovation: Our quantification of innovation assumes equal research productivities in fossil and green energy, $\eta_f = \eta_g \equiv \eta$. We choose η such that, along the asymptotic green path (where all energy innovation is in green technology) A_{gt} grows at 2% per year ($\eta = 5 \ln 1.02 / \ln \gamma = 1.4634$). We also set the exponent parameter $\psi = 0.5$ in line with other models (e.g., Acemoglu, Akcigit, Alp, Bloom, and Kerr 2018) as motivated by empirical evidence of an elasticity of R&D expenditures with respect to R&D costs close to one (e.g., Bloom, Van Reenen, and Williams 2019; Bloom, Griffith, and Van Reenen 2002, etc.).

[28] One may be concerned about the implications of methane leaks and other life-cycle emissions (e.g., coal mine methane). A comprehensive Department of Energy analysis of greenhouse gas emissions in the US energy sector suggests slightly higher CO_2-equivalent emissions coefficients ($\xi_c = 1.124$, $\xi_s = 0.489$) but a similar ratio of coal-to-gas emissions per kWh once life-cycle emissions of both fuels are taken into account (Skone et al. 2016) . To the extent that our calibration underestimates natural gas-related warming differentially, our estimates of the shale gas boom's negative impacts on emissions may be a lower bound.

We quantify BAU innovation subsidies based on the National Science Foundation's (NSF) Industrial Research and Development Survey, which until 2007 offered a breakdown of private and government-supported R&D spending in the United States by energy technology category. On average during the model base years available in the data (2006-07), 3.85% of R&D spending in the fossil-fuel sector was funded by the government, leading us to set $q_{f0} = 0.0385$. For green technology, we take the total R&D spending-weighted average subsidy rate across renewables (13.9%) and nuclear (0%) in the most recent years with disclosed data (2004-07), yielding $q_{g0} = 0.08$. While such direct evidence on green vs. fossil subsidy rates is not available for subsequent years, we triangulate the evolution of these subsidies based on the NSF's successor Business Enterprise Research and Development (BERD) survey and based on IEA estimates of public US R&D support by energy technology. The data are consistent with similar overall subsidy rates but a slight shift towards green technologies in the subsequent two model periods, leading us to assume $q_{ft} = 0.03$ and $q_{gt} = 0.10$ for $t > 0$ (see Appendix A.7.4 for details).

Climate: We adopt the carbon cycle specification of Golosov et al. (2014) with appropriate modifications for our five-year time periods (see Appendix A.7.4). We also adopt their damage function $(1 - D(S_t)) = e^{-\zeta(S_t - S_0)}$ and consider two potential values for the damage parameter ζ. The first is Golosov, Hassler, Krusell, and Tsyvinski's (2014) benchmark value for deterministic models ($\zeta = 5.3 \cdot 10^{-5}$). The second is a "high" damage specification with doubled doubled damage coeffcient $\zeta = 1.1 \cdot 10^{-4}$. This specification is motivated by recent syntheses of global damage estimates, which point to higher impacts than the earlier literature (e.g., Barrage and Nordhaus 2023; Howard and Sterner 2017).

Since the benchmark model only endogenizes greenhouse gas emissions from the US electricity sector, we additionally specify a path for emissions from other countries and sectors, P_t^{ROW}. We take these emissions to be exogenous in the main analysis but also present an extension allowing spillover effects of the shale gas boom to other sectors and countries. We use BAU emissions projections from the 2010 RICE model for all but one-third of US emissions for this purpose (Nordhaus 2010).[29] [30]

[29]We allocate all but 31.5% of US emissions—corresponding to the average US electricity greenhouse gas emissions share between 1990-2008— to P_t^{ROW} and replace the law of motion for carbon concentration (8) with $S_t = \overline{S} + \sum_{s=0}^{t+T} (\varphi_L + (1 - \varphi_L) \varphi_0 (1 - \varphi_d)^s) \left(P_{t-s} + P_{t-s}^{ROW}\right)$. In Appendix A.8.1, we show the results with emissions spillovers from the US electricity sector to other sources of emissions.

[30]This calibration implies 2100 BAU CO_2 concentrations of 712-728ppm, slightly above the Representative Concentration Pathway 6.0 scenario (implying 670ppm and around 2.2°C warming above 1986-2005 levels by 2100), but well below the 8.5 scenario (implying 936ppm and 3.7°C warming, Collins et al., 2014).

Preferences. Finally, following Barrage and Nordhaus (2023), we consider the benchmark values for the pure rate of social time preference ($\rho = 1\%/yr$) and the intertemporal elasticity of substitution (implying $\vartheta = 1.5$), but we additionally present results for lower discount rates as well. We further assume that consumers may experience disutility from climate change impacts on the rest of the world (ROW), thus replacing (1) with

$$U_t = \sum_{\tau=t}^{\infty} \frac{1}{(1+\rho)^{\tau-t}} \left(\frac{C_\tau^{1-\vartheta}}{1-\vartheta} + \upsilon(S_\tau) \right) \text{ where } \upsilon(S_\tau) \equiv \iota_{ROW} \cdot \varsigma_\tau \cdot (1 - e^{-\zeta(S_\tau - S_0)}), \tag{25}$$

where $\upsilon'(S) \leq 0$, and $\iota_{ROW} \in [0,1]$ is interpreted as an altruism parameter that captures how much US consumers care about global damages. In addition, $(1 - e^{-\zeta(S_t - S_0)})$ is the fraction of global output lost due to carbon concentrations S_t, and ς_t is a time-varying preference parameter set so that, with full altruism ($\iota_{ROW} = 1$), the US utility loss is approximately equivalent to the value of ROW output losses due to climate change (this implies $\varsigma_t \approx (-1) \cdot Y_t^{ROW} \cdot C_t^{-\vartheta}$, as detailed in Appendix A.7.4). This specification implies that with full altruism, the US social planner would set a carbon tax equal to the global social cost of carbon. In our benchmark, we followed the most common approach in policy work and set $\iota_{ROW} = 1$ (e.g., Greenstone, Kopits, and Wolverton 2020). The term $\upsilon(S_t)$ has no impact on the equilibrium analysis and only affects optimal policy. As a result, none of our analysis in the previous section needs to be modified.

Table 4 summarizes this discussion by reporting how each parameter is calibrated.

4.2 Short-Run Impacts

We now present quantitative estimates of the static effects of the shale gas boom. We consider a doubling of B_{s0}. This is motivated by the relative price change of coal and gas observed after the US shale gas boom, which shows a decline in average gas fuel cost relative to coal from 2.8 in the 2006-10 to 1.4 in 2011-15.

Table 5 presents both benchmark results and their sensitivity to a number of variations. As expected, the net effect of an improvement in gas extraction technology on contemporaneous carbon emissions is consistently negative, with a 4.5% decline in emissions in the benchmark calibration. A higher (lower) elasticity of substitution ε between energy types is associated with slightly higher (lower) declines in CO_2 emissions. This is because a higher ε implies stronger substitution from both coal and clean technologies towards natural gas, but the

Table 4—Base Year Model Calibration Summary

Parameter	Value(s)	Meaning, sources, and notes
ε	1.8561	Elasticity of subs. btw. clean, dirty electricity production: Papageorgiou et al. (2017)
λ	0.4	Elasticity of subs. btwn. energy, production input in final goods production: Literature (e.g., Van der Werf, 2008)
ν	0.5	Share parameter on energy in final goods production: Normalized (without loss of generality)
		Generation tax τ_{jt} on energy type j in period t:
τ_{g0}, τ_{g1}	-0.0368, -0.0331	Generation-weighted avg. tax from Lazard levelized costs,
τ_{g2}, (τ_{g3}^{IRA})	-0.0316, (-0.20)	EIA data, Bistline et al. (2023), Casey et al. (2023)
τ_{s0}, τ_{s1}	0.0, 0.005	OECD net effective carbon rate for US electricity gen.,
τ_{s2}, τ_{s3}	0.015, 0.03	gas emissions intensity from EIA
τ_{c0}, τ_{c1}	0.0, 0.015	OECD net effective carbon rate for US electricity gen.,
τ_{c2}, τ_{c3}	0.03, 0.06	coal emissions intensity from EIA
κ_c, κ_s	0.2816, 0.3693	Share parameter on each source in energy aggregator:
κ_g	0.3491	Rationalize electricity demands (EIA) given costs
γ	1.07	Innovation advancement factor: Match profits (Census)
ξ_c, ξ_s	1.001, 0.429	Emissions intensities: EIA (2016, GtCO_2/tril.kWh)
$\widetilde{A}_{E,0}$		Productivity term on energy aggregate: Rationalize final goods producer's initial electricity demand (2006-10)
$A_{g,0}$,$A_{c,0}$,$A_{s,0}$, $B_{c,0}$,$B_{s,0}$,$A_{P,0}$		Initial productivities: Match equilibrium conditions at observed GDP, energy production, and policy/cost estimates
η_B	1.1585	Fossil-fuel extraction productivity growth term: Match BLS data 1.58%/yr (1987-2010)
η	1.4634	Research productivity: Match growth rate of 2%/yr
ψ	0.5	Innovation congestion term: Blundell et al. (2002)
q_{g0}, $q_{gt>0}$	0.08, 0.10	Innovation subsidies: NSF, IEA, modeler's judgment
q_{f0}, $q_{ft>0}$	0.0385, 0.03	Innovation subsidies: NSF, IEA, modeler's judgment
ζ	$5.3 \cdot 10^{-5}$	Climate damages term: Golosov et al. (2014)
ρ	0.01 / year	Pure rate of social time preference: DICE-2023
ϑ	1.5	Consumption elasticity: DICE-2023

Note: This table reports how we choose parameters and initial conditions based on either values from the literature or data moments we try to match.

Table 5—Short-run Effects of the Shale Gas Boom

	$\%\Delta\xi_E$	$\%\Delta E$	$\%\Delta CO_2$
Benchmark	−11.5%	8.0%	−4.5%
Higher $\varepsilon = 2.2$	−13.8%	8.5%	−6.5%
Lower $\varepsilon = 1.5$	−9.2%	7.5%	−2.4%
Higher $\lambda = 0.5$	−11.5%	10.0%	−2.7%
Lower $\lambda = 0.3$	−11.5%	6.0%	−6.2%

Note: This table shows predicted short-run change in emissions intensity (ξ_E), electricity aggregate (E), and CO_2 emissions following a 100% increase in B_{s0} in the benchmark case and for alternative values of the elasticities of substitution across electricity types and between electricity and production. In all cases, the substitution effect is negative and dominates the scale effect.

former shift is more powerful and thus yields lower emissions. A higher (lower) value for the elasticity of substitution λ between the production and energy inputs is associated with a smaller (larger) decline in CO_2 emissions since this increases (decreases) the scale effect—as C_{Et} raises, workers get reallocated toward the production input but less so for a high λ.

It is useful to compare these results to the data and empirical studies of the shale gas boom's impacts. Aggregate data suggest that CO_2 emissions from US electricity generation declined 11.4% between 2006-10 and 2011-15, an almost identical magnitude to our benchmark estimate of -11.5%. Microeconometric studies quantifying short-run effects of natural gas price changes on electricity producers yield similar estimates.[31]

4.3 Dynamic Impacts

We now examine the dynamic effects of a natural gas boom in our model. We specifically introduce the shale gas boom in the 2011-15 period and contrast the evolution of the economy with a counterfactual world where there was no shale gas boom.[32] Given the substantial recent changes in and uncertainty over future BAU policies, we also showcase how the dynamic effects of the boom differ with the introduction of the IRA in the 2020-24 period, assumed to remain in place permanently thereafter.

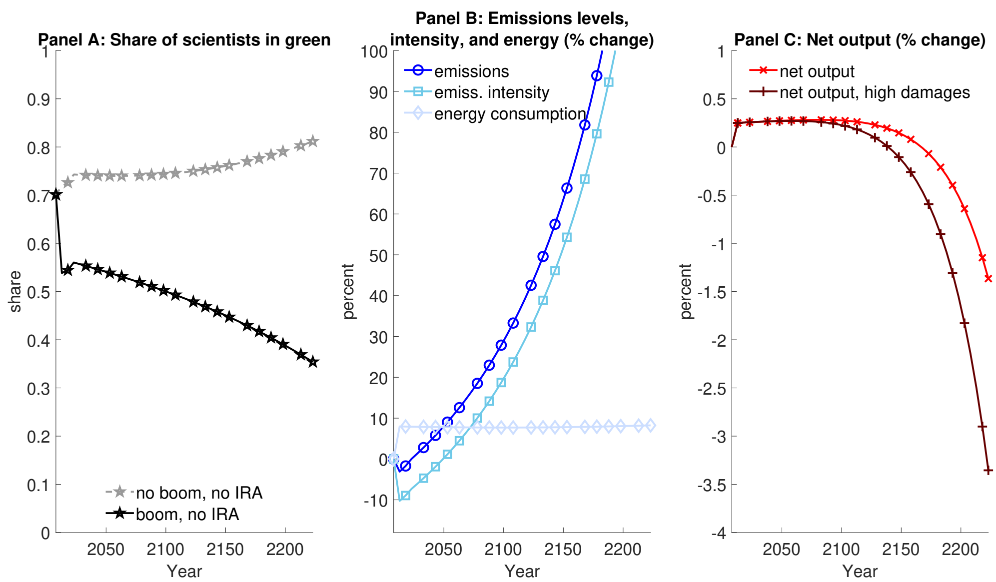
Figures 3 and 4 present the effects of a doubling of B_{s0} and with the IRA, respectively. The central result is that, in both cases, the natural gas boom leads to a persistent setback in green innovation. Without the IRA, the shale gas boom permanently delays a green transition that would have otherwise occurred. This is of course the quantitative equivalent of part 1 of Proposition 4, where the natural gas boom shifts the economy from a green path to a fossil-fuel path, permanently increasing emissions. With the IRA, the economy avoids this "fossil fuel trap" but still faces a persistent reduction of green innovation compared to a counterfactual world without the boom, analogous to part 3 of Proposition 4. Consequently, while the shale gas boom decreases carbon emissions in the short-run, it increases emissions

[31]Cullen and Mansur (2017) estimate that the 2008-12 decline in natural gas pricesled to a 10% reduction in the CO_2 emissions intensity of electricity generation. Linearly extrapolating Linn and Muehlenbachs's (2018) estimate to the observed price reduction suggests an emission intensity decline of 4%. These estimates, which hold factors such as generating capacity constant, are naturally smaller than our five-year aggregate impacts. Other literature estimates are harder to compare to our results as they focus on different outcomes. For example, Knittel, Metaxoglou, and Trindade (2015) compare and CO_2 emissions responses to gas price variation across different types of power plants among entities with both coal- and gas-fired capacity.

[32]In reality, there were other relevant shocks, such as increased production of renewable inputs in China. For this reason, our results should not be viewed as predictive about future trajectories, but as informative about the effects of the shale gas boom relative to a counterfactual without such a boom.

in the long-run. Indeed, the boom's impact on emissions turns positive as early as 2023 both with and without the IRA, and by 2100 they are about 30-35 % higher than in the counterfactual world without the shale gas boom. Panel C of both figures plots impacts on output net of climate damages, which are initially positive but turn substantially negative over time. These negative long-run effects of the boom are mitigated in the IRA scenario, however, as overall emissions levels decline over time with the IRA.

Figure 3—Shale Gas Boom Impact on BAU Outcomes, no IRA

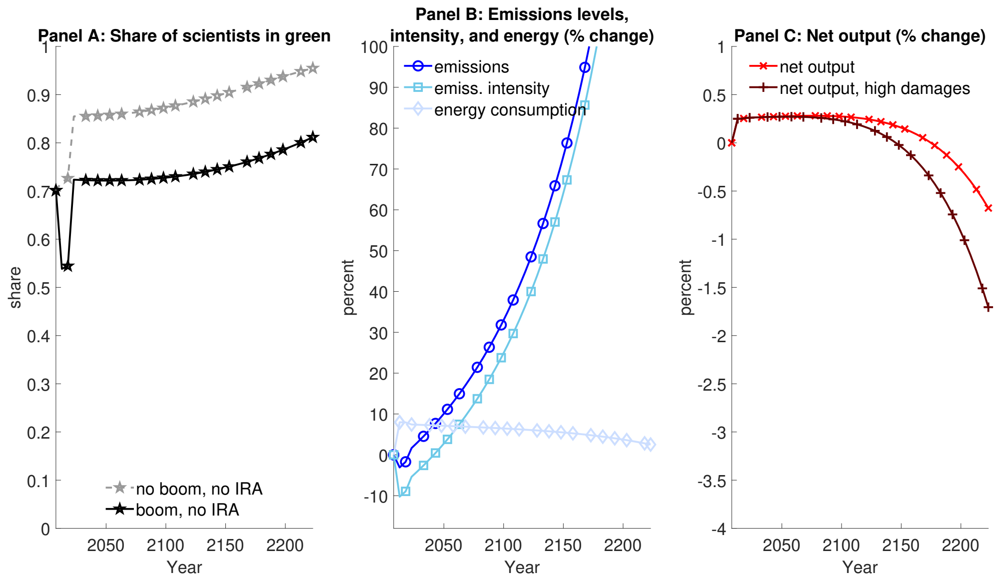


Note: This figure shows the dynamic effects of the shale gas boom in our baseline calibration without the IRA (i.e. holding BAU policies constant after 2020). Panel A depicts the allocation of scientists with and without the shale gas boom. While innovation is increasingly directed toward green technology without the boom, it moves toward fossil-fuel technologies with the boom. Panel B shows the changes (in %) in emission intensity, energy consumption and emissions that result from the boom. The boom is associated with an initial decline in emission intensity that is reversed over time, resulting in an eventual rise in emissions. Panel C shows the effect on net output of the boom for two calibrations of the damage function. The boom eventually decreases net output.

These benchmark results take emissions outside of the US electricity sector as given. In reality, US energy technologies may impact technology and emissions in the rest of the world. We explore this question in Appendix A.8.1 and show that this response can magnify the negative long-run consequences of a US natural gas boom, though a full study of the two-way technology spillovers between countries is beyond the scope of the current paper.

Finally, it is useful to compare the model's predictions to two key untargeted moments in the data, namely the pre- and post-boom ratios of green to fossil fuel patents. The model matches both the 2006-10 level (1.52 in the model vs. 1.47 in the data) and the 2011-15 level (1.08 in the model vs. 1.02 in the data) well, increasing our confidence in the quantitative model and its counterfactual implications.

Figure 4—Shale Gas Boom Impact on BAU Outcomes, with IRA



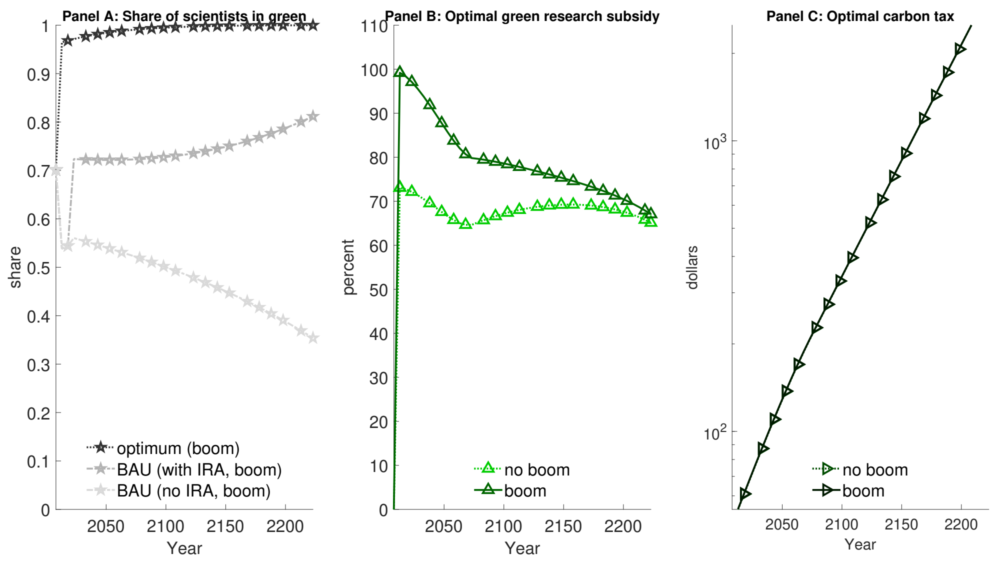
Note: This figure shows the dynamic effects of the shale gas boom in our baseline calibration with the IRA added to BAU policy permanently as of 2020-24. Panel A depicts the allocation of scientists with and without the shale gas boom. While innovation is increasingly directed toward green technology as a result of the IRA, the shale gas boom reduces green innovation persistently compared to a counterfactual without the boom. Panel B shows the changes (in %) in emission intensity, energy consumption and emissions that result from the boom. The boom is associated with an initial decline in emission intensity that is reversed over time. As a result emissions eventually rise following the boom. Panel C shows the effect on net output of the boom for two calibrations of the damage function. The boom eventually decreases net output.

4.4 Policy Implications

We next turn to the optimal policy response the shale gas boom in the US. We focus on the choices of a social planner maximizing discounted US welfare. Recall from Section 3.6 that the optimal allocation can be decentralized using a carbon tax and a green research subsidy (financed or rebated lump-sum), and we focus on these two instruments. The planner takes the path of carbon emissions in the rest of the world and outside of the US electricity sector as given. We maintain the same parameters as in the benchmark calibration throughout, but we replace the BAU policies with the optimal policy.

We start by characterizing the optimal allocation of researchers, after the natural gas boom and focusing on the GHKT formulation of damages. Panel A of Figure 5 compares the share of researchers in green technologies in both BAU scenarios (with and without a permanent version of the IRA) against the optimal allocation. It shows that, while the IRA may be helpful in substantially redirecting innovation efforts towards green technologies especially in the aftermath of the shale gas boom, it still falls far short of the optimum. That is, optimal policy should prioritize research efforts in green technologies even more so than current policy already does. Panels B and C explore how the natural gas boom impacts optimal policy. We see that, consistent with AABH, the optimal clean innovation subsidy is quite high, around 70%, even in the absence of the natural gas boom. Furthermore, the subsidy should increase further, by another 25 percentage points in the early decades of the boom. It is also worth noting that, as Panel C highlights, optimal policy involves a sizable carbon tax that increases over time, though this tax is not very sensitive to the boom. This latter result occurs because, as in GHKT, the optimal carbon price (as a fraction of GDP) depends mainly on damages and the rate of time preference.[33]

Figure 5—Optimal Green Innovation Subsidies and Carbon Prices Over Time



Note: This figure shows the optimal policy. Panel A shows the allocation of scientists in BAU (with and without a permanent version of the IRA) and in the optimum (with the boom). The optimal policy redirects innovation toward green technologies. Panel B shows the optimal clean research subsidy with and without the boom. The subsidy is higher with the boom. Panel C shows the optimal carbon tax with and without the boom, the tax remains similar in both cases.

4.5 Welfare Effects of (Unmanaged) Shale Gas Booms

Finally, we explore whether an unmanaged natural gas boom—meaning without the appropriate policy responses—improves or damages welfare. The results presented in Section 4.3 indicate that, without recent changes in US energy policy, the fossil-fuel trap configuration in part 1 of Proposition 5 would apply in our benchmark calibration, and thus an unmanaged natural gas boom would have unambiguously negative welfare effects (as our

[33]We note two additional points. First, the benchmark GHKT result can be extended to a setting with non-logarithmic CRRA preferences as in our model, in which case consumption growth also affects the optimal carbon tax-GDP ratio (Barrage 2013). Second, the results are similar if we use higher damages than GHKT, except that the initial green subsidy and carbon tax levels are higher in this case.

consumption elasticity parameter is $\vartheta = 1.5$). The results thus far also indicate that, while the IRA may help the US avoid such a "fossil fuel trap," the shale gas boom still increases carbon emissions and lowers net output in the long-run, so that we might still expect negative welfare consequences depending on the time horizon and discounting parameters.

In Table 6 we focus on welfare effects for a standard climate-economy model time horizon of 400 years. We focus on a benchmark rate of social time preference of $\rho^{yr} = 1\%$. From the first row of the table we see that an unmanaged natural gas boom in the context of BAU policies through 2020 is expected to reduce welfare by 1.5% in consumption equivalent terms with the GHKT damages and by 2.7% in the high damages case. The introduction of a permanent version of the IRA could reduce these welfare losses substantially, though they remain sizeable at 0.4% with GHKT damages and 1% in the high damages case. Columns (3) and (4) give the threshold values of time preference below which welfare effects are negative, which range from 1.6% to 2.5% per year across the four cases. Figure 6 plots the welfare effects of the shale gas boom for discount rates between 0.1% and 1%

The next six rows of Table 6 demonstrate that these results are robust to varying the elasticities of substitution ε and λ and the parameter governing the innovation elasticity ψ. While the negative welfare effects fluctuate—from a low of -0.6% to a high of **-4.4%**—the general pattern is very similar to the benchmark in the first row.

The next row of the table shows that if we focus on the effects that completely ignore the rest of the world, then the shale gas boom is close to neutral with the GHKT damages and reduces US welfare by about 0.3% with the high damages.

The remaining four rows confirm that there are significant gains from switching to optimal policy even after the IRA and that these gains increase considerably following the shale gas boom. For example, under GHKT damages, the shale gas boom nearly doubles the stakes of optimizing climate policy, from 1.6% to 3.3% (in consumption equivalent terms) compared to a counterfactual with BAU policies through 2020, and from 0.8% to 1.4% compared to a counterfactual BAU scenario with a permanent version of the IRA from 2021.

5 Extensions

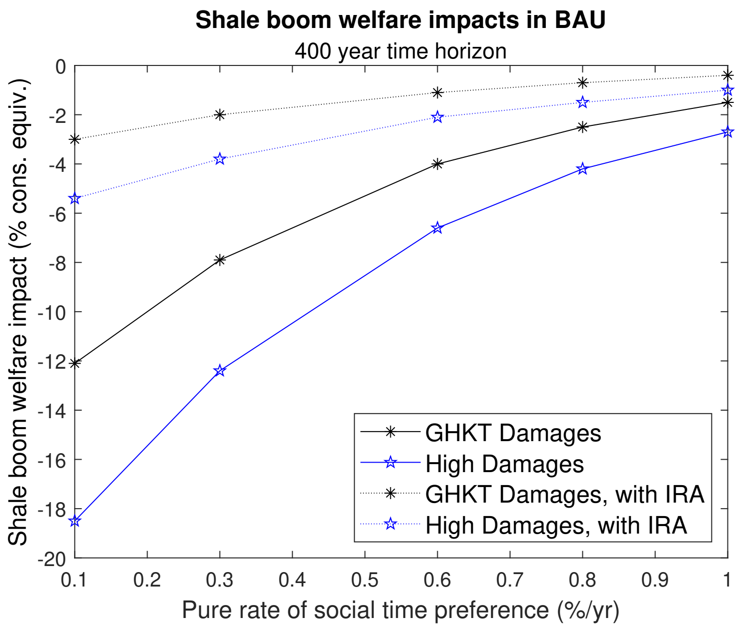
This section briefly discusses some extensions to our theoretical and quantitative analysis.

Table 6—Welfare Effects of the Shale Gas Boom and the Optimal Policy

	Welfare Impacts $\rho^{yr} = 1\%$		Threshold ρ^{yr}	
Damages:	GHKT	High	GHKT	High
Effect of boom in BAU (no IRA unless noted)				
Benchmark	−1.5%	−2.7%	2.0%	2.5%
Benchmark with IRA	−0.4%	−1.0%	1.6%	2.2%
Higher $\varepsilon = 2.2$	−2.5%	−4.4%	2.4%	2.9%
Lower $\varepsilon = 1.5$	−0.6%	−1.2%	1.6%	2.1%
Higher $\lambda = 0.5$	−1.4%	−2.6%	2.1%	2.6%
Lower $\lambda = 0.3$	−1.6%	−2.9%	2.0%	2.5%
Higher $\psi = 0.55$	−1.1%	−2.1%	1.9%	2.3%
Lower $\psi = 0.45$	−1.9%	−3.4%	2.2%	2.7%
No altruism toward ROW	0.1%	−0.3%	0.9%	1.3%
Effect of optimal policy vs. BAU (no boom)	1.6%	3.4%		
Effect of optimal policy vs. BAU (with boom)	3.3%	6.5%		
Effect of optimal policy vs. BAU with IRA (no boom)	0.8%	2.0%		
Effect of optimal policy vs. BAU with IRA (with boom)	1.4%	3.1%		

Note: In the first 9 rows, this table reports, across a range of scenarios, the welfare impacts of the shale gas boom (in consumption equivalent terms) ("Welfare Impacts"), and the threshold on the annual pure rate of social time preference below which these welfare impacts are negative ("Threshold ρ_{yr}"). In both cases the economy is in laissez-faire.In the last 4 rows, the table reports the welfare impact of switching from BAU to the optimal policy across 4 scenarii depending on whether the presence of the shale gas boom and that of the IRA. Welfare is computed for a 400-year time horizon.

Figure 6—Welfare Impacts of the Shale Gas Boom in BAU Across Utility Discount Rates



Note: This figure shows the welfare impacts of the shale gas boom (in consumption equivalent terms) for different values of the pure rate of social time preference, both for the GHKT and the high damages scenarios, **both with and without a permanent version of the IRA**. Welfare is computed for a 400-year time horizon. In all cases, the shale gas boom is associated with welfare losses which increase in absolute value when the pure rate of social time preference is lower and damages are higher.

5.1 Alternative Growth Processes in Extraction

Our analysis so far has focused on the case where extraction technologies grow exogenously at a sufficiently fast rate, ensuring that they do not become a bottleneck on the energy sector. In this subsection, we discuss two alternative scenarios, one in which extraction technologies grow slowly and another one where there is endogenous innovation in extraction.

Slow Progress in Extraction Technologies. We now consider the case where the growth rate of B_{st} and B_{ct} is small. In this scenario, fossil-fuel prices increase rapidly over time so that, eventually, it becomes unprofitable for firms to innovate in power plant technologies for coal and natural gas, and innovation is always redirected to clean energy. Emissions decrease toward zero. Nevertheless, a natural gas boom can still impact emissions and welfare because it encourages innovation in fossil-fuel technologies in the short run. Formally, we establish (proof in Supplementary Material Appendix B.1.4):

Proposition 7 *Assume that Assumption 1 holds, $\varepsilon \geq 2$ and $\eta_B < \eta/\varepsilon$. Then:*

1. There exists a time t_{switch} such that for all $t > t_{switch}$, $s_{gt} > 1/2$ and eventually all innovation takes place in green technologies.

2. A natural gas boom at $t = 1$ delays the time t_{switch} and reduces green innovation until then.

3. For $\ln\gamma$ small, the natural gas boom increases emissions in the long-run and decreases output.

Overall, this case is similar to the third part of Proposition 4 where the economy converges to the green path with or without the boom. More specifically, part 1 of Proposition 7 establishes that the economy always transitions to a green path, but part 2 clarifies that this switch is delayed by the natural gas boom. Finally, part 3 shows that emissions increase in the long-run. In addition, since the economy eventually relies on green technologies, the reduction in green innovation along the transition path reduces output.[34] In Appendix A.8.2, we present quantitative results for this case, focusing on the simple limiting scenario with zero progress in extraction technologies.

Endogenous Innovation in Extraction Technology. Appendix A.6 considers the case of endogenous innovation in extraction technologies. This economy behaves similarly to the one with exogenous fast growth in extraction technologies as it also exhibits path dependence

[34] The assumption $\varepsilon \geq 2$ is a sufficient but not necessary condition for this proposition. It plays a role similar to the assumption that $\min\left\{B_{ct}/A_{c(t-1)}, B_{st}/A_{s(t-1)}\right\} > \gamma^{\eta_f}/(\varepsilon - 1)$ used in Proposition 3. We also make the technical assumption that $\ln\gamma$ is small for part 3, which is useful in proving that following the boom, green technologies decrease at all future dates.

in green versus fossil-fuel innovations. We prove the equivalent of Proposition 3 for this economy, establishing that a natural gas boom (an exogenous increase in B_{s0}) decreases innovation in the green technology A_{g1} relative to fossil-fuel innovation, and that when $\varepsilon C_{s0} \geq B_{s0}$, it also reduces green innovation in absolute terms.

5.2 An Extended Quantitative Model

This subsection considers an extended version of our quantitative model. We present a brief overview of the two key changes we implement here and refer the reader to Appendix A.9 for details. First, we allow natural gas and coal to be more substitutable with each other than with renewables, for example, because of the intermittency of renewables. Namely, we now assume that the energy composite E_t is produced as

$$E_t = \left(\left(\kappa_c E_{ct}^{\frac{\sigma-1}{\sigma}} + \kappa_s E_{st}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1} \frac{\varepsilon-1}{\varepsilon}} + \kappa_g E_{gt}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{26}$$

where $\sigma \geq \varepsilon$ is the elasticity of substitution between coal and gas. In the quantitative implementation, we keep the benchmark elasticity between clean and dirty fuels ($\varepsilon = 1.8561$) and set $\sigma = 2$ in line with the coal-gas electricity elasticity of substitution in empirical studies and other quantitative models (e.g., Bosetti et al. 2007; Ko and Dahl 2001; Söderholm 1998)

Second, we relax the assumption that all fossil-fuel innovations apply equally to coal and gas power plants. Instead, each innovation in coal-based power plants is coal-specific with probability $1-\chi$ but can also be used in natural gas power plants with probability χ, and vice-versa. We choose the benchmark parameter χ so that the extended model matches the observed ratio of green to fossil-fuel patents in the pre-boom period (2006-10), which yields $\chi = 0.92$.[35] This estimate is consistent with the fact that many intermediates are shared between gas and coal generation (e.g., boilers, steam engines, super-heaters, etc., see, e.g., discussion in Lanzi, Verdolini, and Hascic 2011). We also consider lower values of χ to gauge the importance of coal-gas innovation spillovers for the results.

Our baseline model is a special case of this extended model with $\varepsilon = \sigma$ and $\chi = 1$. Proposition 1 on the short-run effects of the natural gas boom can be extended to this setup with minor modifications (see Proposition A.5 in Appendix A.9). We find that a natural gas boom is more likely to lead to a short-run reduction in emissions in this case as the

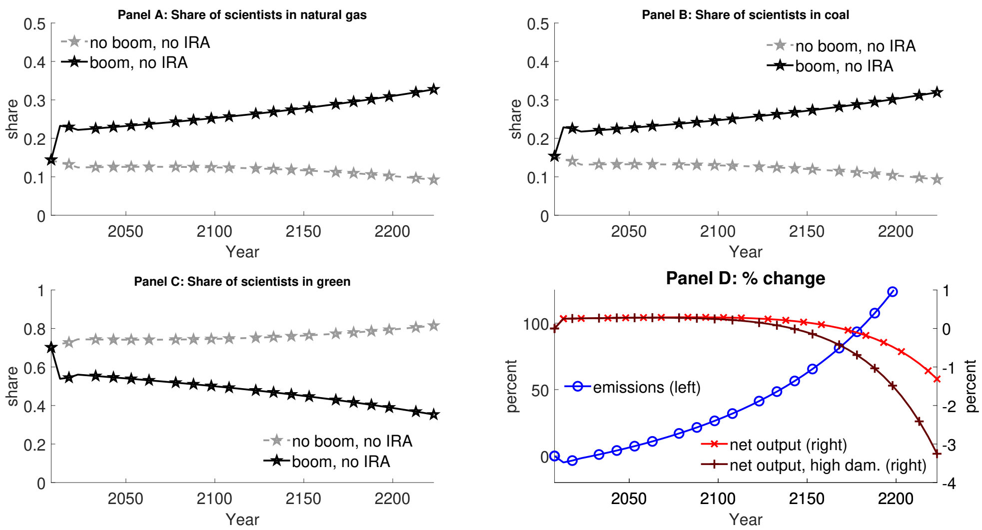
[35]We also assume BAU fossil fuel R&D subsidy rates are equal for coal and gas innovations.

substitution effect between fossil fuels is larger.

In Appendix A.9, we derive explicit conditions under which the natural gas boom reduces green innovation (see Proposition A.6). We further show that with $\chi < 1$, a shale gas boom favors natural gas-based over coal-based innovations, and this tends to reduce emissions in the medium-run relative to our benchmark economy (since natural gas is cleaner than coal).

Figure 7 presents the impacts of the natural gas boom in our extended quantitative model in the case without the IRA. Results for the case with the IRA are presented in Appendix A.9. In both cases, the boom reduces carbon emissions and increases output in the short run, but leads to an extended delay in the green transition, raising emissions and reducing net output in the long run. Interestingly, the welfare impacts of the natural gas boom are similar to our benchmark model. Finally, while assuming away innovation spillovers between coal and natural gas mitigates the negative welfare effects of the shale gas boom in BAU, the results are qualitatively and quantitatively robust to values substantially lower than in the benchmark (e.g., $\chi = 0.31$, see Appendix A.9).

Figure 7—Shale Gas Boom Impacts in the Extended Model



Note: This figure shows the dynamic effects of the shale gas boom in laissez-faire in the extended model. Panel A depicts the share of scientists allocated to natural gas power plant technologies with and without the shale gas boom. Panel B and C do same for scientists allocated to coal power plant technologies and green technologies, respectively. While innovation is increasingly directed toward green technologies without the boom, it moves toward fossil-fuel technologies with the boom. Panel D shows the changes (in %) in emissions and in net output that result from the boom. The boom increases emissions in the long-run and decreases net output.

5.3 Complementarity between Natural Gas and Renewable

Renewables are intermittent energy sources, and this can introduce some complementarity between them and natural gas, the production of which can be ramped up and down easily.[36] Our model in Section 5.2 already captures this complementarity to some degree, since it allows for $\sigma > \varepsilon$—which implies greater complementarity between renewables and natural gas than between the two fossil fuels. In Supplementary Material Appendix B.4, we present an alternative model with a hybrid energy source, combining renewables and natural gas. We show with this extended model that a natural gas boom now leads to a greater reduction of emissions in the short-run, but continues to reduce green innovations for reasonable parameter values (which we confirm with a brief quantitative exercise).

6 Conclusion

Engineering a transition from fossil fuels to renewables and other cleaner sources of energy is one of the major challenges of the current generation. One question is how energy sources with intermediate CO_2 emissions, such as natural gas, should be used in this process. These sources can reduce emissions in the short run, but it remains an open question whether they would help or hinder the longer-run transition.

This paper investigates the short- and long-term effects of a natural gas boom in an economy where energy can be produced with coal, natural gas, or a clean energy source, and innovation can be directed either toward fossil-fuel or clean energy. In the short run, a natural gas boom reduces CO_2 emissions under plausible conditions but it also discourages clean innovations. We document that empirically the US shale gas boom was indeed associated with a notable decline in the ratio of green relative to fossil-fuel electricity patents. We show that because of this negative effect on innovation, a natural gas boom may increase long-run emissions and reduce welfare – in the most extreme case leading to a "fossil-fuel trap" by permanently shifting the economy from a green to a fossil-fuel path.

We calibrate our model to the US electricity sector and find that the shale gas boom reduces emissions in the short-run but raises them in the longer run. However, policies matter: Had BAU policies remained at their pre-IRA levels, the US economy would be in the range of parameters and initial conditions for a fossil-fuel trap. In contrast, with the IRA,

[36] Once better storage technologies are developed, this source of complementarity may be weakened.

the shale gas boom still leads to a persistent setback in green innovation and a medium-run increase in emissions but the economy remains on a green transition path. In both cases, for reasonable values of the social rate of time preference, the shale gas boom reduces long-run welfare — even though, with the optimal policies, it could have massively improved welfare. Our findings thus highlight the need for appropriate climate policy responses to the shale boom – in general in the form of a substantially higher clean research subsidy.

There are several research directions suggested by our study. First, our analysis assumed that there was no similar natural gas boom in the rest of the world. In practice, natural gas production increased in other countries as well and shale gas is likely to spread to other parts of the world. Incorporating these into a more detailed model with cross-country trade and innovation linkages is an area for future study. Second, we note that the lessons of our model may be relevant to other "intermediate solutions" to the energy transition problem. Several of the proposed solutions, including biofuels, fission nuclear energy or geoengineering, also raise the possibility of other types of environmental damages, and a more general model incorporating different types of environmental externalities may be necessary to study their long-run implications. More generally, our analysis suggests that the use of natural gas as a solution to the climate change challenge may have much in common with other historical episodes that accidentally but permanently directed innovation toward potentially inefficient solutions. Examples may include the use of a uranium cycle instead of a thorium cycle in nuclear fission, or Henry Ford's technology choices for mass production which enabled internal combustion engines to replace early electric vehicles. Developing models for the study of the short-run vs. long-run trade-offs when technology can be directed to different technology classes or platforms is another major area of research.

References

Acemoglu, D. (1998). "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality". *Quarterly Journal of Economics* 113.4, pp. 1055–1089.

— (2002). "Directed Technical Change". *Review of Economic Studies* 69.4, pp. 871–809.

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hémous (2012). "The Environment and Directed Technical Change". *The American Economic Review* 102 (1), pp. 131–166.

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr (2018). "Innovation, Reallocation, and Growth". *American Economic Review* 108.11, pp. 3450–3491.

Acemoglu, D., U. Akcigit, D. Hanley, and W. Kerr (2016). "The Transition to Clean Technology". *Journal of Political Economy* 124.1, pp. 52–104.

Aghion, P., R. Bénabou, R. Martin, and A. Roulet (2023). "Environmental Preferences and Technological Choices: Is Market Competition Clean or Dirty?" *American Economic Review: Insights* 5 (1).

Aghion, P., A. Dechezleprêtre, D. H. Hémous, R. Martin, and J. van Reenen (2016). "Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry". *Journal of Political Economy* 124.1, pp. 1–51.

Arkolakis, C. and C. Walsh (2023). *Clean Growth*. Tech. rep. National Bureau of Economic Research.

Barrage, L. (2013). "Sensitivity Analysis for Golosov, Hassler, Krusell, and Tsyvinski (2013): Optimal Taxes on Fossil Fuel in General Equilibrium". *Technical Notes*.

Barrage, L. and W. D. Nordhaus (2023). "Policies, Projections, and the Social Cost of Carbon: Results from the DICE-2023 Model". *NBER Working Paper* 3112.

Bistline, J., N. Mehrotra, and C. Wolfram (2023). *Economic implications of the climate provisions of the Inflation Reduction Act*. Tech. rep. National Bureau of Economic Research.

Bloom, N., J. Van Reenen, and H. Williams (2019). "A Toolkit of Policies to Promote Innovation". *Journal of economic perspectives* 33.3, pp. 163–184.

Bloom, N., R. Griffith, and J. Van Reenen (2002). "Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979–1997". *Journal of Public Economics* 85.1, pp. 1–31.

Bosetti, V., E. Massetti, and M. Tavoni (2007). "The WITCH Model: Structure, Baseline, Solutions".

Brown, S. P. A. and A. Krupnick (Aug. 27, 2010). "Abundant Shale Gas Resources: Long-Term Implications for U.S. Natural Gas Markets". *RFF Working Paper Series* dp-10-41.

Burtraw, D., K. Palmer, A. Paul, and M. Woerman (Mar. 22, 2012). *Secular Trends, Environmental Regulation, and Electricity Markets*. Resources for the Future.

Cai, Y. and T. S. Lontzek (2019). "The Social Cost of Carbon with Economic and Climate Risks". *Journal of Political Economy* 127.6, pp. 2684–2734.

Calel, R. and A. Dechezleprêtre (2016). "Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market". *Review of Economics and Statistics* 98.1, pp. 173–191.

Carvalho, M., A. Dechezleprêtre, and M. Glachant (2017). "Understanding the Dynamics of Global Value Chains for Solar Photovoltaic Technologies".

Casey, G. (2023). "Energy Efficiency and Directed Technical Change: Implications for Climate Change Mitigation". *Review of Economic Studies*, rdad001.

Casey, G., W. Jeon, and C. Traeger (2023). "The Macroeconomics of Clean Energy Subsidies".

Collins, M. et al. (2014). "Long-term Climate Change: Projections, Commitments and Irreversibility". *Climate Change 2013–The Physical Science Basis*, pp. 1029–1136.

Cullen, J. A. and E. T. Mansur (2017). "Inferring Carbon Abatement Costs in Electricity Markets: A Revealed Preference Approach Using the Shale Revolution". *American Economic Journal: Economic Policy* 9.3, pp. 106–33.

Daubanes, J., F. Henriet, and K. Schubert (2021). "Unilateral CO2 Reduction Policy with More than One Carbon Energy Source". *Journal of the Association of Environmental and Resource Economists* 8.3.

Dechezleprêtre, A. and M. Glachant (2014). "Does Foreign Environmental Policy Influence Domestic Innovation? Evidence from the Wind Industry". *Environmental and Resource Economics* 58.3, pp. 391–413.

Energy Information Administration (2016). *Frequently Asked Questions*. URL: https://www.eia.gov/tools/faqs/faq.php?id=74&t=11 (visited on 03/2023).

Energy Information Administration (2019). *Annual Energy Outlook*. URL: https://www.eia.gov/outlooks/archive/aeo19/ (visited on 03/2023).
— (2021). *How Much Coal Is Left*. URL: https://www.eia.gov/energyexplained/coal/how-much-coal-is-left.php (visited on 03/2023).
— (2022). *How Much Natural Gas Does the United States Have, and How Long Will It Last?* URL: https://www.eia.gov/tools/faqs/faq.php?id=58&t=8 (visited on 03/2023).
Fell, H. and D. T. Kaffine (2018). "The Fall of Coal: Joint Impacts of Fuel Prices and Renewables on Generation and Emissions". *American Economic Journal: Economic Policy* 10.2, pp. 90–116.
Fried, S. (2018). "Climate Policy and Innovation: A Quantitative Macroeconomic Analysis". *American Economic Journal: Macroeconomics* 10.1, pp. 90–118.
Gentile, C. (2024). "Relying on Intermittency: Clean Energy, Storage, and Innovation in a Macro Climate Model".
Gillingham, K. and P. Huang (2019). "Is Abundant Natural Gas a Bridge to a Low-Carbon Future or a Dead-End?" *The Energy Journal* 40.2.
Gillingham, K., R. G. Newell, and W. A. Pizer (2008). "Modeling Endogenous Technological Change for Climate Policy Analysis". *Energy Economics* 30.6, pp. 2734–2753.
Golosov, M., J. Hassler, P. Krusell, and A. Tsyvinski (2014). "Optimal Taxes on Fossil Fuel in General Equilibrium". *Econometrica : journal of the Econometric Society* 82, pp. 41–88.
Greaker, M., T.-R. Heggedal, and K. E. Rosendahl (2018). "Environmental Policy and the Direction of Technical Change". *The Scandinavian Journal of Economics* 120.4, pp. 1100–1138.
Greenstone, M. (2024). "The Economics of the Global Energy Challenge". *AEA Papers and Proceedings* 114, pp. 1–30.
Greenstone, M., E. Kopits, and A. Wolverton (2020). "Developing a Social Cost of Carbon for US Regulatory Analysis: A Methodology and Interpretation". *Review of Environmental Economics and Policy*.
Greenstone, M. and I. Nath (2021). "U.S. Energy & Climate Roadmap". Energy Policy Instiute at the University of Chicago.
Harstad, B. and K. Holtsmark (2024). *The Gas Trap: Outcompeting Coal vs. Renewables*. Tech. rep. National Bureau of Economic Research.
Hassler, J., P. Krusell, and C. Olovsson (2021). "Directed Technical Change as a Response to Natural Resource Scarcity". *Journal of Political Economy* 129.11, pp. 3039–3072.
Hémous, D. (2016). "The Dynamic Impact of Unilateral Environmental Policies". *Journal of International Economics* 103, pp. 80–95.
Hémous, D. and M. Olsen (2021). "Directed Technical Change in Labor and Environmental Economics". *Annual Review of Economics*.
Henriet, F. and K. Schubert (2019). "Is Shale Gas a Good Bridge to Renewables? An Application to Europe". *Enivronmental and Resource Economics* 72, pp. 721–762.
Holladay, J. S. and J. LaRiviere (2017). "The Impact of Cheap Natural Gas on Marginal Emissions from Electricity Generation and Implications for Energy Policy". *Journal of Environmental Economics and Management* 85.205-227.
Howard, P. H. and T. Sterner (2017). "Few and Not so Far between: A Meta-Analysis of Climate Damage Estimates". *Environmental and Resource Economics* 68.1, pp. 197–225.
International Energy Agency (2019). *The Role of Gas in Today's Energy Transitions*. URL: https://www.iea.org/reports/the-role-of-gas-in-todays-energy-transitions (visited on 03/2023).

Kavlak, G., J. McNerney, and J. Trancik (2018). “Evaluating the Causes of Cost Reduction in Photovoltaic Modules”. *Energy Policy* 123, pp. 700–710.
Knittel, C., K. Metaxoglou, and A. Trindade (2016). “Are We Fracked? The Impact of Falling Gas Prices and the Implications for Coal-to-Gas Switching and Carbon Emissions”. *Oxford Review of Economic Policy* 32.2, pp. 241–259.
Knittel, C. R., K. Metaxoglou, and A. Trindade (2015). “Natural Gas Prices and Coal Displacement: Evidence from Electricity Markets”.
Ko, J. and C. Dahl (2001). “Interfuel Substitution in US Electricity Generation”. *Applied Economics* 33.14, pp. 1833–1843.
Lanzi, E., E. Verdolini, and I. Hascic (2011). “Efficiency-Improving Fossil Fuel Technologies for Electricity Generation: Data Selection and Trends”. *Energy Policy* 39, pp. 7000–14.
Lemoine, D. (2024). “Innovation-led transitions in energy supply”. *American Economic Journal: Macroeconomics* 16.1, pp. 29–65.
Linn, J. and L. Muehlenbachs (2018). “The Heterogeneous Impacts of Low Natural Gas Prices on Consumers and the Environment”. *Journal of Environmental Economics and Management* 89, pp. 1–28.
McJeon, H. et al. (2014). “Limited Impact on Decadal-Scale Climate Change from Increased Use of Natural Gas”. *Nature* 514.7523, pp. 482–485.
Nordhaus, W. D. (1994). *Managing the Global Commons: The Economics of Climate Change*. MIT Press. Cambridge, Massachusetts.
— (2010). “Economic Aspects of Global Warming in a Post-Copenhagen Environment”. *Proceedings of the National Academy of Sciences* 107.26, pp. 11721–11726.
Papageorgiou, C., M. Saam, and P. Schulte (2017). “Substitution between Clean and Dirty Energy Inputs: A Macroeconomic Perspective”. *The Review of Economics and Statistics* 99.2, pp. 281–290.
Peters, M., M. Schneider, T. Griesshaber, and V. H. Hoffmann (2012). “The Impact of Technology-Push and Demand-Pull Policies on Technical Change–Does the Locus of Policies Matter?” *Research Policy* 41.8, pp. 1296–1308.
Popp, D. (2002). “Induced Innovation and Energy Prices”. *The American Economic Review* 92.1, pp. 160–180.
Popp, D., J. Pless, I. Hascic, and N. Johnstone (2022). “Innovation and Entrepreneurship in the Energy Sector”. Ed. by S. S. A. Chatterki J. Lerner and M. Andrews. University of Chicago Press, pp. 175–248.
Skone, T. J. et al. (2016). *Life Cycle Analysis of Natural Gas Extraction and Power Generation*. National Energy Technology Laboratory (NETL), Pittsburgh, PA, Morgantown, WV.
Smulders, S. and M. de Nooij (2003). “The Impact of Energy Conservation on Technology and Economic Growth”. *Resource and Energy Economics* 25, pp. 59–79.
Söderholm, P. (Jan. 1, 1998). “The Modelling of Fuel Use in the Power Sector: A Survey of Econometric Analyses”. *Journal of Energy Literature* IV:2.
Van der Werf, E. (2008). “Production functions for climate policy modeling: An empirical analysis”. *Energy economics* 30.6, pp. 2964–2979.
Yu, Y., H. Li, Y. Che, and Q. Zheng (2017). “The Price Evolution of Wind Turbines in China: A Study Based on Themodified Multi-Factor Learning Curve”. *Renewable Energy* 103, pp. 522–536.

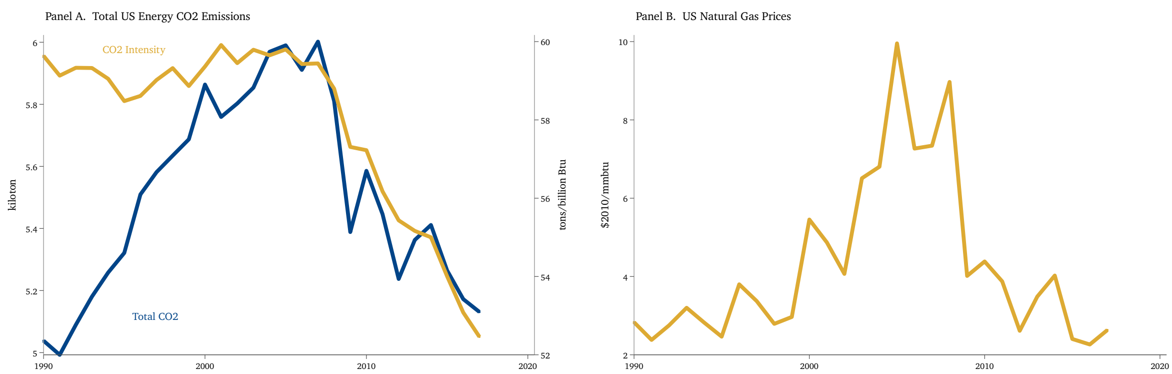
A. Online Appendix for "Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Boom"

A.1 Additional Empirical Results

This section provides additional empirical results, which complement those presented in the Introduction and in Section 2.

Further Results on Emission and Patenting Trends. We first note that total primary energy consumption and total energy CO_2 emissions behave very similarly to the trends shown in Figure 1 Panel C for the electricity sector. This is depicted in Figure A.1 Panel A (data are from the US Energy Information Administration). Next, Figure A.1 Panel B verifies the sharp decline in US natural gas prices during the shale gas boom period (data are from the World Bank and the Bureau of Labor Statistics).

Figure A.1—Emissions for the Whole US Economy and Natural Gas Prices

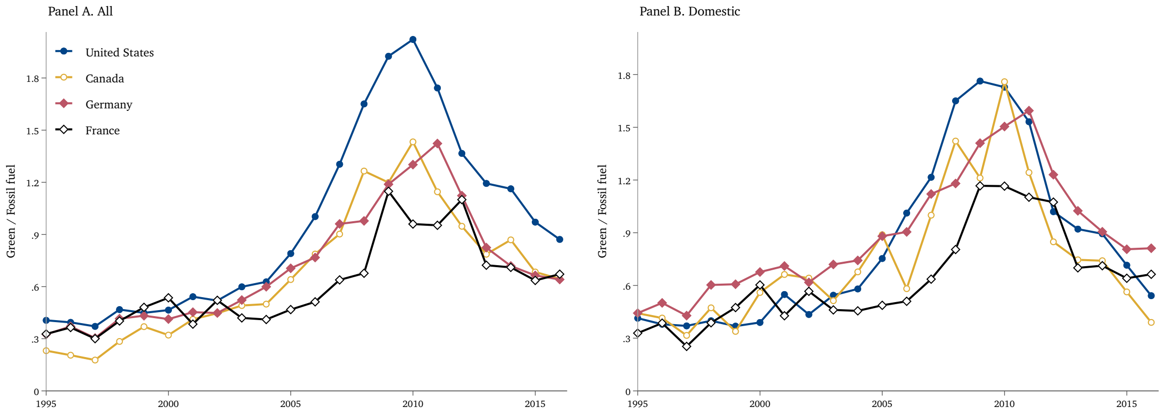


Note: Panel A reports the emission intensity (emissions divided by total energy consumption) and the total emissions of the entire US economy (data source: EIA). Both decrease sharply after the shale gas boom. Panel B reports the US natural gas price, which also collapses after the boom.

Next, Figure A.2 reproduces Figure 2 but for the ratio of green over fossil-fuel patents, leading to similar patterns. In unreported results, we verified that the patterns are similar when (renewable or green) patents are weighted by citations.[1]

[1]We can also look at clean and fossil-fuel electricity patents separately by taking the ratio over total patents. The ratios of clean (renewable or green) patents over total patents display a hump-shape pattern with a peak around 2010 (see also Figure 1.D for the US). The trends are less clear-cut for fossil-fuel electricity patents over total patents. Since these trends may be dominated by variations in other sectors with fast patenting growth (such as IT) and since our interest is in the direction of innovation within the electricity sector, we focus on the ratios of clean patents relative to fossil-fuel electricity patents.

Figure A.2—Ratio of Green to Fossil-Fuel Patents Across Countries



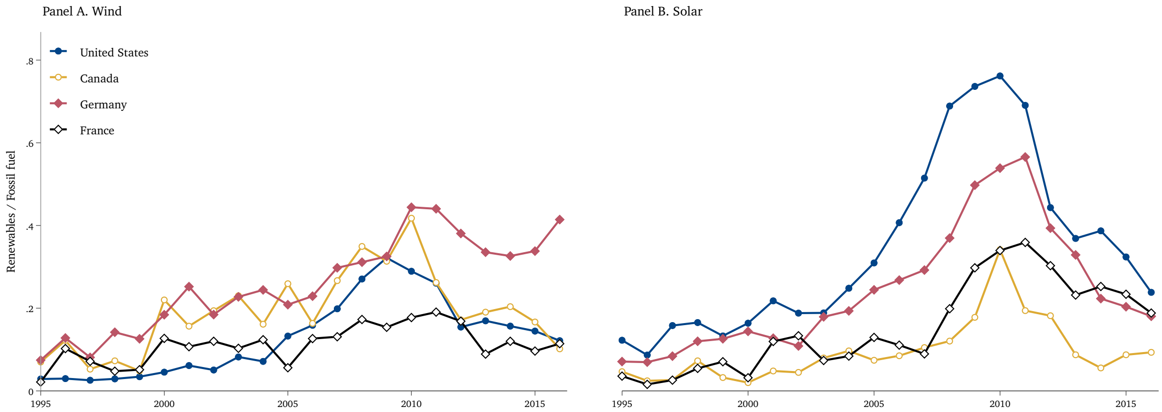
Note: This figure reports the ratio of green (= renewables + nuclear + biofuel) to fossil-fuel patents in the US, Canada, France and Germany (data source: PATSTAT). Patents are allocated to countries according to their patent office. In Panel A, we count all patents, while in Panel B, we only count patents by domestic inventors (allocating patents fractionally if inventors from multiple countries are listed). The reversal in innovation occurs in all four countries.

Figure A.3 unpacks renewable technologies and separately shows the ratio of wind power over fossil-fuel patents (panel A) and the ratio of solar photovoltaic over fossil-fuel patents (panel B) for domestic inventions. The pattern for wind power is less pronounced than for solar and there is no consistent decline in France and Germany after 2010. This suggests that at least for wind power, the factors behind the recent decline in renewable innovations are stronger in North America than in the United States. We also looked at the ratio of storage patents (Y02E70/30) over fossil-fuel patents. We found a relative decline in storage patents, though with a slight delay (from 2013 instead of 2011 for renewables). This is consistent with the decline in green innovations spilling over to storage technologies, which is a complementary input. Yet, these series are noisier due to the relatively low number of storage patents.[2]

Further Results on Panel Regressions. Table A.1 presents robustness checks for Table 1. We start from the specification of column 6 in the baseline table where the dependent variable is the $\sinh^{-1}$ difference between green and fossil-fuel patents. In these specifications, we count domestic patents only and we include all of our controls. Column (1) removes the year fixed effects, which leads to a somewhat larger coefficient. Column (2) does not weigh observations by country size. The coefficient remains of a similar magnitude but becomes

[2]Within fossil-fuel electricity patents, one can also distinguish between energy saving patents (which can be considered "grey" innovations since they allow to reduce the use of fossil fuel to produce fossil-fuel electricity) and others. We did not find a clear trend-break around 2010 in the direction of innovation within fossil-fuel electricity patents.

Figure A.3—Ratio of Wind and Solar Patents to Fossil-Fuel Patents across Countries



Note: This figure reports the ratio of wind (Panel A) or solar pv (Panel B) to fossil-fuel patents in the US, Canada, France and Germany (data source: PATSTAT). Patents are allocated to countries according to their patent office. We only count patents by domestic inventors (allocating patents fractionally if inventors from multiple countries are listed). While solar innovations decrease markedly for all countries following the boom, wind innovations only do so in the US and Canada.

less precise. Column (3) uses the log difference instead of the $\sinh^{-1}$ difference, leading to similar estimates (though we lose a few observations with zero green or fossil-fuel patents). Column (4) focuses on granted patents for which the results are slightly stronger. Column (5) weighs patents by the number of citations received. Column (6) uses only renewable patents instead of all green patents. Column (7) replaces the real gas price index from the IEA with the IEA wholesale price index deflated by the GDP deflator (from OECD data), which is available for a smaller set of countries. In all three cases, the coefficient on gas prices remains very similar.

A.2 Uniqueness of Equilibrium and Proof of Proposition 3

We can rewrite (21) as:

$$f\left(s_{gt}, A_{c(t-1)}, B_{ct}, A_{s(t-1)}, B_{st}, C_{g(t-1)}\right) = 1 \tag{A-1}$$

where the function f is defined as

$$f \equiv \frac{\left(\frac{\gamma^{-\eta_f s_{ft}^{1-\psi}}}{A_{c(t-1)}}\kappa_c^{\varepsilon}\left(\frac{\gamma^{-\eta_f s_{ft}^{1-\psi}}}{A_{c(t-1)}} + \frac{1}{B_{ct}}\right)^{-\varepsilon} + \frac{\gamma^{-\eta_f s_{ft}^{1-\psi}}}{A_{s(t-1)}}\kappa_s^{\varepsilon}\left(\frac{\gamma^{-\eta_f s_{ft}^{1-\psi}}}{A_{s(t-1)}} + \frac{1}{B_{st}}\right)^{-\varepsilon}\right)s_{gt}^{\psi}}{\kappa_g^{\varepsilon} C_{g(t-1)}^{\varepsilon-1} s_{ft}^{\psi} \gamma^{\eta_g s_{gt}^{1-\psi}(\varepsilon-1)}}. \tag{A-2}$$

Table A.1—Robustness Checks

	No Y FE	Unweighted	Log	Granted	Citation weighted	Renewable over FF	Wholesale
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln(Gas Price Index)	0.52	0.31	0.23	0.50	0.21	0.25	0.24
	(0.07)	(0.24)	(0.12)	(0.15)	(0.11)	(0.12)	(0.05)
ln(GDP/capita)	1.95	1.05	3.04	2.64	3.10	2.25	2.05
	(0.16)	(1.06)	(0.99)	(1.30)	(0.98)	(1.14)	(1.03)
ln(Public R&D Fossil)	−0.05	−0.01	−0.06	−0.18	−0.07	−0.06	−0.14
	(0.04)	(0.05)	(0.04)	(0.07)	(0.04)	(0.07)	(0.05)
ln(Public R&D Green)	0.26	−0.10	0.01	0.04	0.03	−0.03	−0.01
	(0.10)	(0.08)	(0.10)	(0.11)	(0.10)	(0.11)	(0.06)
ln(Energy consumption)	0.03	−0.65	−0.42	−0.51	−0.35	−0.09	0.95
	(0.55)	(0.60)	(0.84)	(0.79)	(0.75)	(1.00)	(0.59)
Year fixed effects		✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓	✓
R-squared	0.76	0.66	0.90	0.84	0.90	0.89	0.94
Observations	608	618	479	618	479	618	226
Countries	29	29	27	29	27	29	13

Note: This table considers deviations from our baseline specification (column (6) of Table 1, see Table 1 notes for further details): a panel regression of the $\sinh^{-1}$ difference between the number of green patents in a country and the number of fossil-fuel patents on the log gas price and controls. Only domestic patents are included and the independent variables are lagged by 2 periods. Column (1) removes the year fixed effects. Column (2) runs an unweighted regression. Column (3) replaces the $\sinh^{-1}$ difference with the log difference, dropping the zeros in this case. Column (4) restricts attention to granted patents, rather than patent applications. Column (5) weighs patent applications by citations. Column (6) looks at renewable patents only (and adjusts weights accordingly). Column (7) uses a wholesale price index to measure gas prices. All regressions include country fixed effects, Columns (2)-(7) also include year fixed effects. Standard errors are clustered at the country-level.

This implies

$$\begin{aligned}
\frac{\partial \ln f}{\partial \ln s_{gt}} &= \psi - \eta(\varepsilon-1)(1-\psi)(\ln\gamma)s_{gt}^{1-\psi} + \psi\frac{s_{gt}}{s_{ft}} \\
&\quad + \frac{\eta(1-\psi)\ln(\gamma)\frac{s_{gt}}{s_{ft}^{\psi}}\left(\kappa_c^{\varepsilon}\frac{C_{ct}^{\varepsilon}}{A_{ct}}\left(1-\varepsilon\frac{B_{ct}}{B_{ct}+A_{ct}}\right)+\kappa_s^{\varepsilon}\frac{C_{st}^{\varepsilon}}{A_{st}}\left(1-\varepsilon\frac{B_{st}}{B_{st}+A_{st}}\right)\right)}{\kappa_c^{\varepsilon}\frac{C_t^{\varepsilon}}{A_{ct}}+\kappa_s^{\varepsilon}\frac{C_{st}^{\varepsilon}}{A_{st}}} \\
&\geq \psi - \eta(\varepsilon-1)(1-\psi)(\ln\gamma)s_{gt}^{1-\psi} + \left(\psi - \eta(\varepsilon-1)(1-\psi)(\ln\gamma)s_{ft}^{1-\psi}\right)\frac{s_{gt}}{s_{ft}}.
\end{aligned}$$

Therefore, we get that $\frac{\partial \ln f}{\partial \ln s_{gt}} > 0$ if Assumption 1 holds. In that case, since $f(0,.) = 0$ and $\lim_{s_g \to 1} f(s_g,.) = \infty$, (21) defines a unique equilibrium innovation allocation.

We have $\frac{\partial f}{\partial B_{st}} > 0$ so that an increase in B_{s1} leads to a lower value for s_{g1}.

Further, we have $\frac{\partial f}{\partial C_{g(t-1)}} < 0$, so that a higher value for $C_{g(t-1)}$ leads to more clean innovation. Then, we get

$$\frac{\partial \ln f}{\partial \ln A_{c(t-1)}} = \frac{\frac{1}{A_{ct}}\kappa_c^\varepsilon C_{ct}^\varepsilon}{\frac{1}{A_{ct}}\kappa_c^\varepsilon C_{ct}^\varepsilon + \frac{1}{A_{st}}\kappa_s^\varepsilon C_{st}^\varepsilon}\left(\varepsilon \frac{B_{ct}}{B_{ct} + \gamma^{\eta s_{ft}^{1-\psi}} A_{c(t-1)}} - 1\right).$$

Therefore $\frac{\partial \ln f}{\partial \ln A_{c(t-1)}} \geq 0$ for all values of s_{ft} provided that $\frac{B_{ct}}{A_{c(t-1)}} > \frac{\gamma^\eta}{\varepsilon - 1}$. Similarly, $\frac{\partial \ln f}{\partial \ln A_{s(t-1)}} \geq 0$ for all values of s_{ft} provided that $\frac{B_{st}}{A_{s(t-1)}} > \frac{\gamma^\eta}{\varepsilon - 1}$. If these conditions are satisfied, then an increase in B_{s1} leads to higher values of A_{s1}, A_{c1} and a lower value of C_{g1}, which imply a lower value of s_{g2}. This in turns leads to even higher values of A_{s2}, A_{c2} and a lower value for C_{g2}. By iteration, all s_{gt} decrease for $t \geq 1$.

A.3 Long-run Dynamics for General η_B

With exogenous growth in extraction technologies and for A_{Pt} growing at the rate $\gamma^{\eta_P} - 1$, the long-run behavior of the economy is characterized by the following two propositions which, respectively, deal with the case where $\varepsilon \geq 2^{1-\psi}$ and the case where $1 < \varepsilon < 2^{1-\psi}$.

Proposition A.1 *Assume that $\varepsilon \geq 2^{1-\psi}$ and that Assumption 1 holds.*

1. If $\frac{\eta_B}{\eta} < \frac{1}{\varepsilon}$, then the economy always converges to a green path where asymptotically all innovation occurs in green technologies.

2. If $\frac{\eta_B}{\eta} > \frac{1}{\varepsilon}$ and i) $\varepsilon \geq 2$ or ii) $\frac{\eta_B}{\eta} \notin \left(\frac{1}{2^{1-\psi}}, \frac{1}{\varepsilon}\left(1 + (\varepsilon - 1)^{\frac{1}{\psi}}\right)^\psi\right)$, then, depending on initial technology levels, the economy converges either to a path where all innovation asymptotically occurs in fossil-fuel technologies, or to a path where all innovation occurs in green technologies (except for an unstable knife-edge case with an interior allocation of innovation in the limit).

3. If $\varepsilon < 2$ and $\frac{\eta_B}{\eta} \in \left(\frac{1}{2^{1-\psi}}, \frac{1}{\varepsilon}\left(1 + (\varepsilon - 1)^{\frac{1}{\psi}}\right)^\psi\right)$, then, depending on initial technology levels, the economy converges either (i) to a path where all innovation asymptotically occurs in fossil-fuel technologies, or (ii) to a path where fossil-fuel technologies develop faster than clean technologies and both exhibit positive growth rates in the long-run, or ()iii) to a path where all innovation occurs in green technologies (except for two unstable knife-edge cases with interior allocations of innovation in the limit).

The first case is characterized by slow growth in extraction technologies (including no growth, $\eta_B = 0$), as in Section 5.1. The second case displays bang-bang long-run behavior. This occurs if growth in extraction technologies is sufficiently fast, as in Section 3.5. The third case, obtained for intermediate values of η_B/η when $\varepsilon < 2$, features an interior and stable asymptotic steady state on top of the fossil-fuel and green paths.

Proposition A.2 *Assume that $\varepsilon < 2^{1-\psi}$ and that Assumption 1 holds. Then:*

1. If $\frac{\eta_B}{\eta} < \frac{1}{2^{1-\psi}}$, then the economy always converges to a green path where, asymptotically, all innovation occurs in green technologies.

2. If $\frac{1}{2^{1-\psi}} < \frac{\eta_B}{\eta} < \frac{1}{\varepsilon}$, then, depending on initial technology levels, the economy converges either to a path where all innovation asymptotically occurs in green technologies, or to a path where fossil-fuel technologies develop faster than clean technologies and both exhibit positive growth rates in the long-run (except for an unstable knife-edge case with an interior allocation of innovation in the limit).

3. If $\frac{1}{\varepsilon} < \frac{\eta_B}{\eta} < \frac{1}{\varepsilon}\left(1+(\varepsilon-1)^{\frac{1}{\psi}}\right)^{\psi}$, then, depending on initial technology levels, the economy converges either (i) to a path where all innovation asymptotically occurs in fossil-fuel technologies, or (ii) to a path where fossil-fuel technologies develop faster than clean technologies and both exhibit positive growth rates in the long-run, or (iii) to a path where all innovation occurs in green technologies (except for two unstable knife-edge cases with interior allocations of innovation in the limit).

4. If $\frac{\eta_B}{\eta} > \frac{1}{\varepsilon}\left(1+(\varepsilon-1)^{\frac{1}{\psi}}\right)^{\psi}$, then, depending on initial technology levels, the economy converges either to a path where all innovation asymptotically occurs in fossil-fuel technologies, or to a path where all innovation occurs in green technologies (except for an unstable knife-edge case with an interior allocation of innovation in the limit).

In the first case, growth in extraction technologies is slow and all innovation is allocated to green technologies asymptotically. In the second case, which only occurs for $\varepsilon < 2^{1-\psi}$, the asymptotic fossil-fuel steady state is interior. The third case is analogous to case 3 in Proposition A.1. The fourth case features bang-bang long-run behavior, and occurs under sufficiently fast growth in extraction technologies, as in Section 3.5.

The proofs of these two Propositions are in our Supplementary Material Appendix B.1.1.

A.4 Proof of Proposition 4

The proof of Proposition 4 proceeds in five steps. First, we establish two lemmas, which are then used in the rest of the proof. Then, we show the existence of thresholds on A_{g0} that determine the long-run behavior of the economy. We then look at the effect of the boom on innovation. Finally, we derive the consequences of the boom for emissions. We also establish that $\overline{\eta} = \frac{1}{2^{1-\psi}}$ for $\varepsilon \geq 2$ and $\overline{\eta} = \max\left(\frac{1}{2^{1-\psi}}, \frac{1}{\varepsilon}\left(1+(\varepsilon-1)^{\frac{1}{\psi}}\right)\right)$ if $\varepsilon < 2$; and that the shale gas boom decreases green innovation when $A_{g0} < \underline{A}_{g0}$ as long as $s_{ft} \leq \left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$. Both statements are mentioned in the text.

Lemma A.1 *Assume that Assumption 1 holds, that* $\min\{B_{c1}/A_{c0}, B_{s1}/A_{s0}\} > \gamma^{\eta}/(\varepsilon-1)$ *and that* B_{ct} *and* B_{st} *grow exogenously at the rate* $\gamma^{\eta_B}-1$. *Then an increase in* B_{s1} *or a decrease in* A_{g0} *is associated with a decline in* s_{gt} *as long as* $s_{f\tau} \leq \left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$ *for all* $\tau \in [1, t-1]$.

Proof. Assume that $s_{f\tau} \leq \left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$ for all $\tau \in [1, t-1]$. Then given that inequality $\min\left\{B_{c\tilde{\tau}}/A_{c(\tilde{\tau}-1)}, B_{s\tilde{\tau}}/A_{s(\tilde{\tau}-1)}\right\} > \gamma^{\eta_f}/(\varepsilon-1)$ holds for $\tilde{\tau} = 1$, it must also hold for all $\tau \in [1, t]$. Proposition 3 establishes that an increase in B_{s1} decreases green innovation, and the same logic applies following a decrease in A_{g0}. ■

Lemma A.2 *Assume that* $s_{ft} > \left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$ *and* $\frac{\eta_B}{\eta} \geq 2^{\psi-1}$, $s_{f\tau} > \left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$ *for all* $\tau \geq t$.

Proof. Consider the equilibrium allocation of scientists first. Let us denote $f_\tau\left(s_g\right) \equiv f\left(s_g, A_{c(\tau-1)}, B_{c\tau}, A_{s(\tau-1)}, B_{s\tau}, C_{g(\tau-1)}\right)$, where f is defined in (A-2), so that the equilibrium allocation obeys $f_\tau\left(s_{g\tau}\right) = 1$. We then obtain:

$$
\begin{aligned}
f_{\tau+1}\left(1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}\right) &= \frac{\frac{\gamma^{-\eta_B}}{A_{c\tau}}\kappa_c^{\varepsilon}\left(\frac{\gamma^{-\eta_B}}{A_{c\tau}}+\frac{\gamma^{-\eta_B}}{B_{c\tau}}\right)^{-\varepsilon} + \frac{\gamma^{-\eta_B}}{A_{s\tau}}\kappa_s^{\varepsilon}\left(\frac{\gamma^{-\eta_B}}{A_{s\tau}}+\frac{\gamma^{-\eta_B}}{B_{s\tau}}\right)^{-\varepsilon}}{\kappa_g^{\varepsilon}A_{g\tau}^{\varepsilon-1}\gamma^{(\varepsilon-1)\left(\eta^{\frac{1}{1-\psi}}-\eta_B^{\frac{1}{1-\psi}}\right)^{1-\psi}}}\left(\frac{1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}}{\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}}\right)^{\psi} \\
&= \frac{\frac{\kappa_c^{\varepsilon}}{A_{c\tau}}\left(\frac{1}{A_{c\tau}}+\frac{1}{B_{c\tau}}\right)^{-\varepsilon} + \frac{\kappa_s^{\varepsilon}}{A_{s\tau}}\left(\frac{1}{A_{s\tau}}+\frac{1}{B_{s\tau}}\right)^{-\varepsilon}}{\gamma^{(\varepsilon-1)\eta_B\left[\left(\left(\frac{\eta}{\eta_B}\right)^{\frac{1}{1-\psi}}-1\right)^{1-\psi}-1\right]}\kappa_g^{\varepsilon}A_{g\tau}^{\varepsilon-1}}\left(\frac{1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}}{\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}}\right)^{\psi}
\end{aligned}
$$

With $\frac{\eta}{\eta_B} \geq 2^{\psi-1}$, we get that $\left(\left(\frac{\eta}{\eta_B}\right)^{\frac{1}{1-\psi}}-1\right)^{1-\psi} < 1$, so that $\gamma^{(\varepsilon-1)\eta_B\left[\left(\left(\frac{\eta}{\eta_B}\right)^{\frac{1}{1-\psi}}-1\right)^{1-\psi}-1\right]} < 1$. This implies

$$
f_{\tau+1}\left(1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}\right) \geq \frac{\frac{\kappa_c^{\varepsilon}}{A_{c\tau}}\left(\frac{1}{A_{c\tau}}+\frac{1}{B_{c\tau}}\right)^{-\varepsilon} + \frac{\kappa_s^{\varepsilon}}{A_{s\tau}}\left(\frac{1}{A_{s\tau}}+\frac{1}{B_{s\tau}}\right)^{-\varepsilon}}{\kappa_g^{\varepsilon}A_{g\tau}^{\varepsilon-1}}\left(\frac{1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}}{\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}}\right)^{\psi} = f_\tau\left(1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}\right).
$$

If $s_{f\tau} > \left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$, then we get that $f_\tau\left(1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}\right) > f\left(s_{g\tau}\right) = 1$ (since f_τ is increasing in g).

This immediately implies that $f_{\tau+1}\left(1-\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}\right)>1$ so that $s_{f(\tau+1)}>\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$. Therefore if $s_{ft}>\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$, then $s_{f\tau}>\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$ for all $\tau\geq t$. ■

Thresholds. Assume that either (i) $\varepsilon\geq 2$ and $\frac{\eta_B}{\eta}>2$, which also implies that $\frac{\eta_B}{\eta}>\frac{1}{\varepsilon}$; or (ii) that $\varepsilon<2$ and $\frac{\eta_B}{\eta}>\max\left\{\frac{1}{2^{1-\psi}},\frac{1}{\varepsilon}\left(1+(\varepsilon-1)^{\frac{1}{\psi}}\right)\right\}$. Using Propositions A.1 and A.2, we know that, except for a knife edge case, the asymptotic allocation of scientists is either all in green or all in fossil-fuel innovations. Using Lemma A.2, we then get that if at any point in time $s_{ft}>\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$, then s_{ft} must converge to 1.

Consider an equilibrium path where innovation is asymptotically allocated all in green technologies. On that equilibrium path, it must be that $s_{ft}\leq\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$. Using Lemma A.1, we then get that had the initial clean technology A_{g0} been higher, green innovation on that alternative path should be higher as well. Therefore, innovation is also asymptotically allocated entirely to the green technology on this alternative path.

Consider now an equilibrium path where asymptotically all innovation is in fossil-fuel technologies together with an alternative path characterized by a lower green technology A_{g0}. Using Lemma A.1, fossil-fuel innovation is higher on the alternative path as long as s_{ft} remains below $\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$, but if s_{ft} crosses $\left(\frac{\eta_B}{\eta}\right)^{\frac{1}{1-\psi}}$, then innovation is eventually all allocated in fossil-fuel technologies. Therefore, it must be the case that asymptotically all innovation is on fossil-fuel technologies on the alternative path.

This establishes the existence of the threshold $\underline{A_{g0}}$: without the boom, the economy converges to the green path for $A_{g0}>\underline{A_{g0}}$, and to the fossil-fuel path for $A_{g0}<\underline{A_{g0}}$.

Effect of the Shale Gas Boom on Innovation. Assume that $A_{g0}<\underline{A_{g0}}$. Then using Lemma A.1, the shale gas boom reduces green innovation until s_{ft} crosses $(\eta_B/\eta)^{\frac{1}{1-\psi}}$, and the economy converges to the fossil-fuel asymptotic steady state.

Assume that $A_{g0}>\underline{A_{g0}}$, then there are two options: either the economy still converges to the green asymptotic steady state or it converges toward the fossil-fuel asymptotic steady state. This defines a threshold $\overline{A_{g0}}$. If $A_{g0}>\overline{A_{g0}}$, innovation asymptotes the green steady state with or without the boom. In that case, it must be that $s_{ft}<(\eta_B/\eta)^{\frac{1}{1-\psi}}$ at all future dates, and hence the boom reduces green innovation. If $A_{g0}\in\left(\underline{A_{g0}},\overline{A_{g0}}\right)$, the boom decreases green innovation until s_{ft} becomes higher than $(\eta_B/\eta)^{\frac{1}{1-\psi}}$ on the post-boom path. Meanwhile, we always have $s_{ft}<(\eta_B/\eta)^{\frac{1}{1-\psi}}$ on the pre-boom path. Therefore, the boom must always reduce green innovation.

Effect of the Shale Gas Boom on Emissions. Using (14), (15), and (16), we get.

$$P = \left(\xi_c \kappa_c^{\varepsilon} \left(\frac{C_{ct}}{C_{Et}}\right)^{\varepsilon} + \xi_s \kappa_s^{\varepsilon} \left(\frac{C_{st}}{C_{Et}}\right)^{\varepsilon}\right) C_{Et} \frac{\nu^{\lambda} \widetilde{A}_E^{\lambda-1} C_{Et}^{\lambda-1}}{\nu^{\lambda} \widetilde{A}_E^{\lambda-1} C_{Et}^{\lambda-1} + (1-\nu)^{\lambda} A_{Pt}^{\lambda-1}} L. \tag{A-3}$$

If $s_{gt} \to 1$, we get that $C_{ct} \to A_{ct}$, $C_{st} \to A_{st}$ and $C_{Et} \to \kappa_g^{\frac{\varepsilon}{\varepsilon-1}} A_{gt}$ so that:

$$P_t \sim \left(\xi_c \kappa_{ct}^{\varepsilon} A_{ct}^{\varepsilon} + \xi_s \kappa_s^{\varepsilon} A_{st}^{\varepsilon}\right) \kappa_g^{-\varepsilon} A_{gt}^{1-\varepsilon} \frac{\nu^{\lambda} \widetilde{A}_E^{\lambda-1} \kappa_g^{\frac{\varepsilon}{\varepsilon-1}(\lambda-1)} A_{gt}^{\lambda-1}}{\nu^{\lambda} \widetilde{A}_E^{\lambda-1} \kappa_g^{\frac{\varepsilon}{\varepsilon-1}(\lambda-1)} A_{gt}^{\lambda-1} + (1-\nu)^{\lambda} A_{Pt}^{\lambda-1}} L$$

which tends to zero since L_{Et} is bounded, $\xi_c \kappa_c^{\varepsilon} C_{ct}^{\varepsilon} + \xi_s \kappa_s^{\varepsilon} C_{st}^{\varepsilon}$ does not grow exponentially and $A_{gt}^{1-\varepsilon}$ decreases exponentially. If $A_{g0} > \overline{A_{g0}}$, then the boom reduces green innovation, which increases C_{ct} and C_{st} and decreases A_{gt}. The expression on the right-hand side is decreasing in A_{gt}, so emissions increase for t large enough following the boom.

Alternatively if $s_{gt} \to 0$, then C_{ct} and C_{st} grow at the rate $\gamma^{\eta_B} - 1$ and A_{gt} does not grow asymptotically. Therefore C_{Et} also grows at the rate $\gamma^{\eta_B} - 1$. This ensures that ξ_{Et} tends toward a constant. Using that A_{Pt} grows at the rate $\gamma^{\eta} - 1$, we get from (A-3) that P_t grows at the rate $\gamma^{\eta_B} - 1$. Output gross of climate damages also grows at the rate $\gamma^{\eta_B} - 1$. Note finally that we immediately conclude that the shale gas boom increases emissions in the long-run if it switches the economy from a green path to a fossil-fuel path, i.e., when we have $A_{g0} \in \left(\underline{A_{g0}}, \overline{A_{g0}}\right)$. This completes the proof of Proposition 4.

A.5 Proof of Proposition 5

We first derive the asymptotic behavior of output on the green and the fossil-fuel paths. We then establish Proposition 5. In Supplementary Material Appendix B.1.2, we look at welfare effects in the case where $A_{g0} > \overline{A_{g0}}$.

Output. Using (2) and (15), we get that output can be written as:

$$Y_t = e^{-\zeta S_t} \left(\nu^{\lambda} \widetilde{A}_E^{\lambda-1} C_{Et}^{\lambda-1} + (1-\nu)^{\lambda} A_{Pt}^{\lambda-1}\right)^{\frac{1}{\lambda-1}} L. \tag{A-4}$$

On a green path where $s_{gt} \to 1$, S_t asymptotes to a constant since emissions decrease exponentially. In addition C_{Et} asymptotically grows like A_{gt} at the rate $\gamma^{\eta} - 1$, since A_{Pt} also grows at the rate $\gamma^{\eta} - 1$, then Y_t asymptotically grows at the rate $\gamma^{\eta} - 1$.

On a fossil-fuel path where $s_{gt} \to 0$, the growth rate of overall energy productivity C_{Et} is constrained by the growth rate of the extraction technologies, so that C_{Et} asymptotically grows at the rate $\gamma^{\eta_B}-1$. Then, output gross of climate damages $\left(\nu^{\lambda}\widetilde{A}_E^{\lambda-1}C_{Et}^{\lambda-1}+(1-\nu)^{\lambda}A_{Pt}^{\lambda-1}\right)^{\frac{1}{\lambda-1}}$ also grows asymptotically at the rate $\gamma^{\eta_B}-1$, but so do emissions. Therefore, given the exponential net-of-damages function $e^{-\zeta S_t}$, output net of climate damages Y_t converges to 0.

Welfare with $A_{g0}\in\left(\underline{A_{g0}},\overline{A_{g0}}\right)$. We first consider the case where $A_{g0}\in\left(\underline{A_{g0}},\overline{A_{g0}}\right)$. If $\vartheta<1$, then without the boom, the economy is on a green path and the utility flow $\frac{C_\tau^{1-\vartheta}}{1-\vartheta}$ is positive and asymptotically grows at the rate $\gamma^{\eta(1-\vartheta)}-1$. With the boom, the economy is on a dirty path and the utility flow tends to zero. For a sufficiently small discount rate, the utility (1) is then larger without the boom than with the boom.

If $\vartheta>1$, the utility flow converges to zero without the boom. With the boom,

$$\frac{1}{(1+\rho)^{\tau}}\frac{C_\tau^{1-\vartheta}}{1-\vartheta}\sim -K_1e^{K_2\zeta(\vartheta-1)\gamma^{\eta_B\tau}}\left(\frac{\gamma^{\eta_B}}{1+\rho}\right)^{\tau}$$

where K_1 and K_2 are positive constant. Therefore, $\frac{1}{(1+\rho)^{\tau}}\frac{C_\tau^{1-\vartheta}}{1-\vartheta}$ tends to $-\infty$, so that $U=-\infty$ regardless of the discount rate ρ. Therefore, the boom reduces welfare.

If $\vartheta=1$, we have

$$\frac{1}{(1+\rho)^{\tau}}\ln C_\tau=\frac{1}{(1+\rho)^{\tau}}\left[-\zeta S_\tau+\ln\left(\left(\nu^{\lambda}\widetilde{A}_E^{\lambda-1}C_{E\tau}^{\lambda-1}+(1-\nu)^{\lambda}A_{P\tau}^{\lambda-1}\right)^{\frac{1}{\lambda-1}}L\right)\right].$$

Without the boom, the utility flow $\ln C_\tau$ tends toward a term growing linearly, so that $\frac{1}{(1+\rho)^{\tau}}\ln C_\tau$ tends to zero. With the boom, the utility flow $\ln C_\tau$ is asymptotically proportional to $-\zeta S_\tau$ and tends to $-\infty$ at the rate $\gamma^{\eta_B}-1$. Therefore we get that $U=-\infty$ if $\rho<\gamma^{\eta_B}-1$, and more generally, welfare is reduced for sufficiently small ρ.

A.6 Endogenous Innovation in Extraction

We now consider the case where productivities of the extraction technologies, B_{ct} and B_{st}, are endogenous and determined by the allocation of scientists. We denote by s_{ft} the mass of innovators in the fossil-fuel sectors, which can now be separated into s_{Aft} innovators in the fossil-fuel power plant technologies A_{ct} and A_{st} (these innovations still apply to both technologies), s_{Bst} innovators in natural gas extraction technologies B_{st} and s_{Bct} innovators in coal extraction technologies B_{ct}. For all innovations in the fossil-fuel sector we impose for simplicity (and without loss of generality) the same probability of success η_{ft}. Innovations in extraction technologies features the same congestion externality, so that the probability of success is $\eta_f s_{it}^{-\psi}$ for $i \in \{Af, Bc, Bs\}$. Since advancing the average fossil-fuel technology now requires endogenous innovation in both power plant and extraction technologies, we let the productivity of research in green technology, η_g, be potentially different from η_f. This is necessary to ensure that long-run growth of gross output can in principle be the same with both technologies.

Expected profits in green innovations and fossil-fuel power plant technologies are still respectively given by (19) (with η_g instead of η) and by (20) (with s_{Aft} instead of s_{ft} and η_f instead of η). Expected profits in extraction technologies are given by:

$$\Pi_{Bct} = \eta_f s_{Bct}^{-\psi} \left(1 - \frac{1}{\gamma}\right) \frac{C_{ct}}{B_{ct}} p_{ct} E_{ct} \text{ and } \Pi_{Bst} = \eta_f s_{Bst}^{-\psi} \left(1 - \frac{1}{\gamma}\right) \frac{C_{st}}{B_{st}} p_{st} E_{st}.$$

In equilibrium, expected profits are equalized for the 4 innovation activities. This leads to equations determining the allocation of innovation within fossil-fuel technologies:

$$\left(\frac{s_{Bct}}{s_{Aft}}\right)^{\psi} = \frac{\frac{C_{ct}}{B_{ct}} \kappa_c^{\varepsilon} C_{ct}^{\varepsilon-1}}{\frac{C_{ct}}{A_{ct}} \kappa_c^{\varepsilon} C_{ct}^{\varepsilon-1} + \kappa_s^{\varepsilon} \frac{C_{st}}{A_{st}} C_{st}^{\varepsilon-1}} \text{ and } \left(\frac{s_{Bst}}{s_{Aft}}\right)^{\psi} = \frac{\frac{C_{st}}{B_{st}} \kappa_s^{\varepsilon} C_{st}^{\varepsilon-1}}{\frac{C_{ct}}{A_{ct}} \kappa_c^{\varepsilon} C_{ct}^{\varepsilon-1} + \frac{C_{st}}{A_{st}} \kappa_s^{\varepsilon} C_{st}^{\varepsilon-1}}, \tag{A-5}$$

and the allocation of innovation between green and fossil-fuel technologies:

$$\left(\frac{s_{Aft}}{s_{gt}}\right)^{\psi} = \frac{\eta_f \left(\kappa_c^{\varepsilon} \frac{C_{ct}}{A_{ct}} C_{ct}^{\varepsilon-1} + \frac{C_{st}}{A_{st}} \kappa_s^{\varepsilon} C_{st}^{\varepsilon-1}\right)}{\eta_g \kappa_g^{\varepsilon} A_{gt}^{\varepsilon-1}}. \tag{A-6}$$

Since it is possible to improve the extraction technology, this case is similar in spirit to that of high growth in extraction technologies, and in Supplementary Material Appendix B.2, we establish the following proposition.

Proposition A.3 *There is path dependence in fossil-fuel versus green innovation.*

We now look at the short-run effects of a natural gas boom on innovation. We assume that $\ln \gamma$ is small so that the three equations in (A-5) and (A-6) define a unique equilibrium and that one can ignore the dependence of the right-hand sides of (A-5) and (A-6) on the innovation allocation when taking comparative statics with respect to changes in technology levels. In Supplementary Material Appendix B.2, we establish:

Proposition A.4 *Suppose that* $\ln \gamma$ *is small. Then an exogenous increase in* B_{s0} *reduces green innovation relative to fossil-fuel power plant innovation. If* $\varepsilon C_{s0} \geq B_{s0}$*, it also reduces green innovation absolutely.*

A.7 Calibration and Electricity Producer Data

In this section, we provide further information on the calibration of parameters.

A.7.1 Accounting for Local Pollution Abatement

Due to regulations such as the Clean Air Act and the Clean Water Act, US power plants are already subject to a range of command-and-control regulations that enforce expenditures to control emissions of local pollutants such as sulfur dioxides, nitrogen oxides, and fly ash (for coal plants).

Formally, we denote by P_i^l local pollution of energy resource i, by ξ_i^l the baseline local pollution intensity, and by μ_i the share of local emissions abated, so that $P_i^l = (1-\mu_i)\xi_i^l R_i$. We assume that to abate a share μ_i of its local emissions, the producer of energy resource i needs to use an additional $\Lambda(\mu_i)$ units of power plant inputs. We denote by $\underline{\mu_i}$ the mandated minimum level of pollution abatement and assume that it is binding. Then, the profit-maximizing input choices of energy producer of type i satisfy $R_i = E_i$ and $Q_i = \left(1 + \Lambda\left(\underline{\mu_i}\right)\right) R_i$. The equilibrium price of energy type i is then given by (23) where we define $\overline{\Lambda_i} \equiv \Lambda\left(\underline{\mu_i}\right)$. Our previous results naturally extend to this case, with A_i replaced by $\frac{A_i}{1+\overline{\Lambda}_i}$—so that we now have $C_i = \left(\frac{1+\overline{\Lambda}_i}{A_i} + \frac{1}{B_i}\right)^{-1}$ for $i \in \{s, c\}$.

A.7.2 Accounting for BAU policies

The presence of ad valorem taxes for green, coal-based or natural-gas based energy has no effect on the producer prices of each type of energy inputs: so (12) still holds for producer prices, and we still obtain that

$$E_{it} = C_{it} L_{it}. \tag{A-7}$$

However, it affects the demand for the different types of electricity by the energy composite producers leading to relative demands given by (24).

Cost minimization then directly implies that the price of energy is still given by $p_{Et} =$

$\gamma w_t / C_{Et}$ but with C_{Et} now obeying:

$$C_{Et} = \left(\frac{\kappa_g^{\varepsilon} A_{gt}^{\varepsilon-1}}{(1+\tau_{gt})^{\varepsilon-1}} + \frac{\kappa_c^{\varepsilon} C_{ct}^{\varepsilon-1}}{(1+\tau_{ct})^{\varepsilon-1}} + \frac{\kappa_s^{\varepsilon} C_{st}^{\varepsilon-1}}{(1+\tau_{st})^{\varepsilon-1}} \right)^{\frac{1}{\varepsilon-1}}. \tag{A-8}$$

Next, we solve for the labor allocation. Using (24) and (A-7), we get the labor allocation in the energy sector as

$$L_{ct} = \frac{\kappa_c^{\varepsilon} C_{ct}^{\varepsilon-1}}{(1+\tau_{ct})^{\varepsilon}} L_{Et},\ L_{st} = \frac{\kappa_s^{\varepsilon} C_{st}^{\varepsilon-1}}{(1+\tau_{st})^{\varepsilon}} L_{Et} \text{ and } L_{gt} = \frac{\kappa_g^{\varepsilon} C_{gt}^{\varepsilon-1}}{\left(1+\tau_{gt}\right)^{\varepsilon}} L_{Et}.$$

Combining these expressions with (3) implies that

$$E_t = \widetilde{C}_{Et} L_{Et} \text{ with } \widetilde{C}_{Et} \equiv C_{Et}^{\varepsilon} \left[\frac{\kappa_c^{\varepsilon} C_{ct}^{\varepsilon-1}}{(1+\tau_{ct})^{\varepsilon}} + \frac{\kappa_s^{\varepsilon} C_{st}^{\varepsilon-1}}{(1+\tau_{st})^{\varepsilon}} + \frac{\kappa_g^{\varepsilon} A_{gt}^{\varepsilon-1}}{(1+\tau_{gt})^{\varepsilon}} \right]^{-1}. \tag{A-9}$$

The first order conditions for the final good producers are given by

$$p_{Et} = (1 - D(S_t))^{\frac{\lambda-1}{\lambda}} \nu \widetilde{A}_E^{\frac{\lambda-1}{\lambda}} E_t^{-\frac{1}{\lambda}} Y_t^{\frac{1}{\lambda}} \text{ with } p_{Pt} = (1 - D(S_t))^{\frac{\lambda-1}{\lambda}} (1-\nu) Y_{Pt}^{-\frac{1}{\lambda}} Y_t^{\frac{1}{\lambda}}.$$

Taking the ratio and using the prices of the energy aggregate and of the production input, which is still given by $p_{Pt} = \gamma w_t / A_{Pt}$, we obtain:

$$\frac{E_t}{Y_{Pt}} = \widetilde{A}_E^{\lambda-1} \left(\frac{\nu C_{Et}}{(1-\nu) A_{Pt}} \right)^{\lambda}.$$

Finally, using $Y_{Pt} = A_{Pt} L_{Pt}$ and (A-9), we obtain the labor allocation:

$$L_{Et} = \frac{\widetilde{A}_E^{\lambda-1} \nu^{\lambda} C_{Et}^{\lambda} \widetilde{C}_{Et}^{-1}}{\widetilde{A}_E^{\lambda-1} \nu^{\lambda} C_{Et}^{\lambda} \widetilde{C}_{Et}^{-1} + (1-\nu)^{\lambda} A_{Pt}^{\lambda-1}} L \tag{A-10}$$

Further, with research subsidies q_{ft} and q_{gt}, equilibrium in the scientists market gives

$$\frac{\Pi_{ft}}{1-q_{ft}} = \frac{\Pi_{gt}}{1-q_{gt}}, \tag{A-11}$$

where the expressions for expected profits (19) and (20) still hold.

A.7.3 Electricity Generation Cost Data Processing Notes

Production Input Costs. We first obtain estimates of plants' non-fuel generation costs using plant-level micro data from annual FERC Form 1 filings for our base period (2006-2010). The data provide information on plants' capital costs, annual generation, generation costs, fuel input usage, fuel heat content, etc. The data are provided as filed by utilities and can thus contain some errors and pathological observations, such as plants that are not engaged in regular operations during a given year. We exclude plant-years that are inactive, report negative operation and maintenance costs or generally negative generation costs per KWh, and those with missing information on fuel inputs. We also exclude plant-years with reported generation costs in excess of $300/MWh which exceeds even the upper bounds of ranges of typical generation cost estimates and these operations generally appear unusual.[3]

For each plant-year we directly observe operational costs ("OM" for which we consider all non-capital and non-fuel production expenditures, such as on maintenance, engineering, etc.) and the plant's total capital costs (including for land, structures, and equipment). We infer annualized capital expenditures ("CAPEX") assuming a 7% interest rate in line with the literature.[4] We then compute each plant's OM and CAPEX expenditures per KWh of electricity generated by each fuel.[5] Prior to aggregation, we winsorize both OM and CAPEX per KWh at the 1% level and convert all costs into $2010.

Finally, for each year and fuel (e.g., coal in 2006), we compute the generation share-weighted average across plants of OM and CAPEX per MWh for each fuel type in each year, add them, and compute the 5-year average over our base period.

Fuel Resource Costs. Next we quantify plants' fuel resource costs using data from FERC/EIA Forms 423 (2006-07) and EIA Form 923 (2006-10).[6] The data provide fuel costs at the generator-fuel-month level, from which we compute the average cost per British thermal unit (Btu) at the plant-year-fuel level. We merge these data with plant-fuel-year level electricity

[3]For example, in 2006, the median number of hours of load operations reported among the (dropped) excessive average cost plants was only 63.5 hours *per year*, suggesting that most of these plants were not engaged in regular operations.

[4]For example, the EIA NEMS model assumes an average interest rate of 6.2% for the electricity sector (EIA 2022), whereas Lazard's assumptions imply a baseline rate of 9.2% based on a 60/40 split of debt/equity (Lazard, e.g., 2015).

[5]In the data, power plants frequently use multiple fuels. We attribute both electricity generation and costs to the fuels in question (e.g., coal vs. gas) based on their shares in the total heat content of the fuel inputs reported in a given plant-year.

[6]For 2006-07, the data also include EIA Form 906 information. Both these and Form 423 (fuel delivery information) data were consolidated into Form 923 beginning in 2008.

generation and fuel consumption data from Form 923 to calculate fuel costs per MWh of electricity generation. Prior to aggregation, we drop observations with reported negative net electricity generation, winsorize fuel costs per MWh for each fuel type-year (e.g., coal in 2006) at the 1% level, and convert all costs in \$2010. Across all plants, we then calculate the generation-weighted average fuel cost per MWh in 2006-10 for coal and natural gas generation, respectively. Note that EIA Form 923 fuel cost estimates are only available for regulated plants.

Abatement Costs. We quantify local pollution abatement expenditures based on EIA Form 767 (1985-2005) and Form 923 (2008-2010). These are mandatory surveys of both regulated and unregulated power plants. For each plant-year we observe electricity output and fuel inputs at the generator level. We drop plant-years with zero or negative net electricity generation. We assign electricity to fuels based on their heat input shares. For abatement, we attribute both OM and investment outlays for flue gas desulfurization and ash disposal to coal exclusively, and split other costs (e.g., on water abatement) between coal and gas based on their generation shares in each plant-year. We convert all costs into \$2010 and use the perpetual inventory method to construct abatement capital stock estimates (assuming an annual depreciation rate of 10%), which we annualize into CAPEX again assuming a 7% interest rate. We then compute each power plant's annual abatement spending per MWh and compute the generation-share weighted average across plants for coal and gas, respectively.[7] Finally, we combine these estimates with those on general production input costs to compute the share of generation costs due to mandated local pollution abatement ($\overline{\Lambda_i}$) at the fuel-year level. We ultimately wish to quantify this abatement cost share for our model base period of 2006-2010. Unfortunately the EIA did not collect abatement expenditure data in 2006 and 2007. We thus take the average of the estimated year 2005 & 2008-10 data instead.

A.7.4 Calibration of the Parameters and Initial Technologies

Electricity Substitution Parameter λ. In the literature, the elasticity of substitution between electricity and other inputs is commonly modeled as part of a nested production function with both electricity and non-electricity energy. That is, in the background of our framework

[7]The raw data contain some extreme outliers in implied abatement OM costs per MWh for some gas operators. We winsorize the right tail (top 1 percentile) of these observations.

one may imagine a production function:

$$Y=\left\{\gamma_Y(A_PY_P)^{\frac{\sigma_1-1}{\sigma_1}}+(1-\gamma_Y)\left[\gamma_{Elec}E_{Elec}^{\frac{\sigma_2-1}{\sigma_2}}+(1-\gamma_{Elec})E_{NonElec}^{\frac{\sigma_2-1}{\sigma_2}}\right]^{\frac{\sigma_2(\sigma_1-1)}{(\sigma_2-1)\sigma_1}}\right\}^{\frac{\sigma_1}{\sigma_1-1}}. \tag{A-12}$$

We are interested in the elasticities of substitution between the production input and electricity $\sigma_{Y_p,Elec}$ and σ_{Elec,Y_p}. The Morishima elasticities are:[8]

$$\sigma_{Elec,Y_p}=\gamma_{Elec}\cdot\sigma_1+(1-\gamma_{Elec})\cdot\sigma_2 \text{ and } \sigma_{Y_p,Elec}=\sigma_1.$$

The literature provides examples or estimates of the parameters in (A-12). Common values for $\sigma_1\sim\sigma_{KL,E}$ are $0.4-0.5$ (e.g., Chen et al., 2017; Van der Werf, 2008; Böhringer and Rutherford 2008; Bosetti et al., 2007). As various modelers also assume $\sigma_2=0.5$ (e.g., Chen et al., 2017; Bosetti et al., 2007), we would have $\sigma_{Elec,Y_p}=\sigma_{Y_p,Elec}=0.5$ for any value of γ_{Elec}. We ultimately use a slightly lower value of 0.4 in recognition of recent empirical evidence of a near-zero capital-labor and energy substitution elasticities (albeit at the yearly level) presented by Hassler et al. (2021).

Calibration of the Energy Composite. Given our estimated $\kappa's$ and initial electricity prices, we can back out the initial electricity composite quantity and price as follows (measured in trillions of kWhs and costs are measured in \$2010):

$$p_{E,0}=\left(\kappa_g^{\varepsilon}(p_{g,0}(1+\tau_{g,0}))^{1-\varepsilon}+\kappa_s^{\varepsilon}(p_{s,0}(1+\tau_{s,0}))^{1-\varepsilon}+\kappa_c^{\varepsilon}(p_{c,0}(1+\tau_{c,0}))^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}=179.75, \tag{A-13}$$

$$E_0=\left(\kappa_gE_{g,0}^{\frac{\varepsilon-1}{\varepsilon}}+\kappa_sE_{s,0}^{\frac{\varepsilon-1}{\varepsilon}}+\kappa_cE_{c,0}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}=5.51. \tag{A-14}$$

We then solve for $\widetilde{A}_{E,0}$ based on the final goods producer's electricity first order condition:

$$p_{E,0}=\frac{\partial Y_0}{\partial E_0}=(1-D(S(t)))^{\frac{\lambda-1}{\lambda}}Y_0^{\frac{1}{\lambda}}\widetilde{\nu A_{E,0}}^{\frac{\lambda-1}{\lambda}}E_0^{\frac{-1}{\lambda}}\rightarrow\widetilde{A}_{E,0}=1.5066+05. \tag{A-15}$$

Profit Margins and γ Calibration. We calibrate γ based on profits data, specifically to match that profits are a share $1-1/\gamma$ of sectoral income in laissez-faire. We collect data on after-tax profits per dollar of sales for corporations in three relevant industries ("Petroleum and coal products", "All Durable Manufacturing", and "All Wholesale Trade") from the US

[8] Intuitively, they are not symmetric because a change in the price of electricity also changes the relative prices of electricity and non-electricity energy, whereas a change in the price of Y_P does not.

Census Bureau's *Quarterly Financial Report* for 2004-2014. With an average weighted profit share of 6.53%, we obtain $\gamma = 1.07$.

Calibration of Remaining Technologies. To calibrate the initial technology levels, we normalize $L = 10$ and we solve for the remaining 12 unknowns to satisfy the following set of 12 equations at the initial observed GDP Y_0, energy production, policies, and energy prices (we reproduce some equations derived earlier here for clarity):

$$
\begin{aligned}
\text{Unknowns} \quad &: \quad A_{g0}, A_{c0}, A_{s0}, B_{c0}, B_{s0}, C_{c0}, C_{s0}, C_{E0}, A_{P0}, w_0, L_{E0}, L_{P0} \qquad \text{(A-16)}\\
Y_0 &= (1-D(S_0))\left((1-\nu)(A_{P0}L_{P0})^{\frac{\lambda-1}{\lambda}} + \nu\left(\widetilde{A}_{E0}E_0\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}\\
A_{g0} &= \frac{\gamma w_0}{p^q_{g0}}, A_{c0} = \frac{\gamma w_0}{p^q_{c0}}, A_{s,0} = \frac{\gamma w_0}{p^q_{s0}}, B_{c,0} = \frac{\gamma w_0}{p^r_{c0}} \text{ and } B_{s,0} = \frac{\gamma w_0}{p^r_{s0}}\\
C_{c0} &= \left(\frac{1+\overline{\Lambda}_c}{A_{c0}} + \frac{1}{B_{c0}}\right)^{-1} \text{ and } C_{s0} = \left(\frac{1+\overline{\Lambda}_s}{A_{s0}} + \frac{1}{B_{s0}}\right)^{-1}\\
C_{E0} &= \left(\frac{\kappa_g^{\varepsilon}A_{g0}^{\varepsilon-1}}{(1+\tau_{g,0})^{\varepsilon-1}} + \frac{\kappa_c^{\varepsilon}C_{c0}^{\varepsilon-1}}{(1+\tau_{c,0})^{\varepsilon-1}} + \frac{\kappa_s^{\varepsilon}C_{s0}^{\varepsilon-1}}{(1+\tau_{s,0})^{\varepsilon-1}}\right)^{\frac{1}{\varepsilon-1}}\\
E_0 &= C_{E0}^{\varepsilon}\left[\frac{\kappa_c^{\varepsilon}C_{c0}^{\varepsilon-1}}{(1+\tau_{c,0})^{\varepsilon}} + \frac{\kappa_s^{\varepsilon}C_{s0}^{\varepsilon-1}}{(1+\tau_{s,0})^{\varepsilon}} + \frac{\kappa_g^{\varepsilon}A_{g0}^{\varepsilon-1}}{(1+\tau_{g,0})^{\varepsilon}}\right]^{-1} L_{E0}\\
\frac{\gamma w_0}{A_{P0}} &= (1-\nu)(1-D(S(t)))^{\frac{\lambda-1}{\lambda}} Y_0^{\frac{1}{\lambda}}(A_{P,0}L_{P,0})^{\frac{-1}{\lambda}} \text{ with } L_{P0} = 10 - L_{E0}.
\end{aligned}
$$

The resulting parameter values are as follows:

A_{g0}	A_{c0}	A_{s0}	B_{c0}	B_{s0}	C_{c0}	C_{s0}	C_{E0}	$A_{P,0}$	w_0	L_{E0}	L_{P0}
100.3	462.1	450	337.4	119.5	187.4	94.3	40.3	4.8e+03	6.87e+03	0.14	9.86

Calibration of BAU R&D Subsidy Rates. While the NSF's Industrial Research and Development Survey enables us to directly quantify effective subsidy rates by technology type (e.g., renewable vs. fossil fuels) through 2007, we have to infer subsequent subsidy rate changes based on indirect evidence. On the one hand, we use the NSF's successor BERD survey to evaluate whether overall energy sector R&D subsidy rates changed in subsequent years. We specifically compute effective subsidy rates by dividing government (state + federal) provided R&D funding (based on the "Domestic R&D paid for by others and performed by the company, by source of funds, [and] industry" tables) by the sum of publicly and privately provided funding (based on the "Domestic R&D paid for and performed by the company by (...) industry" tables) for NAICS codes 22 (Utilities), 3336 (Engine, turbine, and power transmission equipment), 335 (Electrical equipment, appliances, and components), 324 (Petroleum and coal products), and 21 (Mining, extraction, and support activities). We note that the latter differs from our empirical analysis which excludes patents related to fossil fuel extraction, but we include it here for consistency with the earlier NSF subsidy estimates for the purposes of gauging changes in subsidy rates over time. While there are some fluctuations across individual years, over the 5-year periods of our model, the average effective subsidy rate is broadly stable at around 2% (1.9% in 2008-10, 2.2% from 2011-15, and 1.8% from 2016-20). Next, we consult IEA estimates of total US public support for R&D by technology to gauge changes in the allocation of funding over time. We specifically compute the share of total categorized R&D support (for fossil fuels, renewables, nuclear) going to low carbon energy each year. Here we see a slight increase in the relative allocation towards green energy, up from around 70% in the base period 2006-10 to around 80% thereafter (83% in 2011-15 and 77% in 2016-20).

Calibration of the Carbon Cycle. We adopt the carbon cycle of Golosov et al. (2014), with the following modifications to match our time period and base period. First, a fraction $\varphi_L = 0.2.$ of carbon emissions remains permanently in the atmosphere. Another fraction φ_0 exits the atmosphere within a decade. The remainder decays at rate φ. For the latter, GHKT match an atmospheric half life of 300 years, implying, in our setting, that decay parameter φ should solve $(1-\varphi)^{60} = 0.5$ and hence $\varphi = 0.0115$. For the former, GHKT match the moment that about half of a CO_2 impulse is removed after 30 years. In our setting, this implies $1-\frac{1}{2} = 0.2 + 0.8\varphi_0(1-0.0115)^5$ yielding $\varphi_0 = .3973$. Finally, we update initial carbon stocks to our base period (2006-2010) levels. Total CO_2 concentrations are set to $S_0 = 830$ Gtc based on the 2010 average from the Mauna Loa observatory.[9]

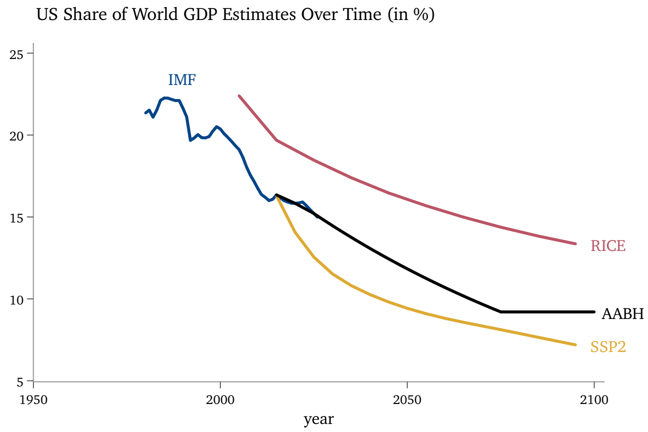
Calibration of Disutility over ROW Climate Damages. The main parameter needed to include rest of the world climate damages in US utility in (25) is ς_t. Conceptually, we would like ς_t to approximate the product of rest of the world output Y_t^{ROW} and the US marginal utility of consumption, which in our model is equivalent to:

[9]Data are from the National Oceanic and Atmospheric Administration's Global Monitoring Laboratory website with URL (accessed December 2021): https://gml.noaa.gov/ccgg/trends/data.html The permanent reservoir is set at GHKT's initial value plus 20% of 2005-2010 global emissions (CDIAC, 2020), yielding $S_{1,0} = 684 + 10 = 694$.[10] The remaining increase in total concentrations is assigned to the second reservoir, $S_{2,0} = 136$ (up from 118 in GHKT).

$$-\varsigma_t = Y_t^{ROW} \cdot (Y_t^{US})^{-\vartheta}. \tag{A-17}$$

Figure A.4 displays different estimates for the US share of world GDP over time based on data and forecasts by the International Monetary Fund (IMF), from the RICE Model (Nordhaus, 2011), and from the Shared Socioeconomic Pathway (SSP) 2 Scenario from the International Institute for Applied Systems Analysis Energy Program.[11]

Figure A.4—Projections of US Share of World GDP



Note: This figure plots the projected US share of World GDP. The historical data and medium-run projections are from the IMF, and projections include those from the RICE model (data source: Nordhaus, 2011), the Shared Socioeconomic Pathway 2 from the IPCC (SSP2, data source: IIASA), and the one we use in our paper (AABH).

We then infer values of ς_t by (i) assuming that US GDP grows 2% per year from its initial value (taken from the data in the first model period of 2011+), (ii) inferring rest-of-the-world GDP based on our predicted US share of World GDP, and (iii) evaluating (A-17) at these values. We note that ς_t is sensitive to the units in which GDP is reported. For our calibration, which reports GDP in 5-year flows of billions of \$2010, its starting value is $\varsigma_{2011-15} = -0.0223$.

A.8 Further Quantitative Results

We now present a few additional quantitative results

[11]We specifically consult the IMF's World Economic Outlook October 2021 projections of "GDP based on PPP, share of the world", available at URL (accessed October 2021): `https://www.imf.org/external/datamapper/PPPSH@WEO/OEMDC/ADVEC/WEOWORLD`. The SSP database is available at (accessed December 2021): `https://tntcat.iiasa.ac.at/SspDb`. All projections are in PPP-adjusted dollars. We adopt an intermediate approach which uses the available IMF forecasts through 2025, assumes that the US share of world GDP declines at 1% per year thereafter until 2075, and then stabilizes at 9.2%.

A.8.1 Spillover Effects

This section presents results for a variant of our benchmark model which allows for spillover effects of the shale gas boom to non-electricity emissions in the United States and to the rest of the world (ROW). Intuitively, we might expect electrification of other sectors (e.g., transportation) to be affected by both changes in electricity prices and in terms of emissions. Moreover, shale extraction technology may also spill over to other countries and perhaps more importantly, even if the ROW does not use shale gas, than there may be spillovers from the redirection of US innovation in the electricity sector toward fossil fuels (i.e. the increase in A_{ct} and A_{st} with a decrease in A_{gt} in the US).

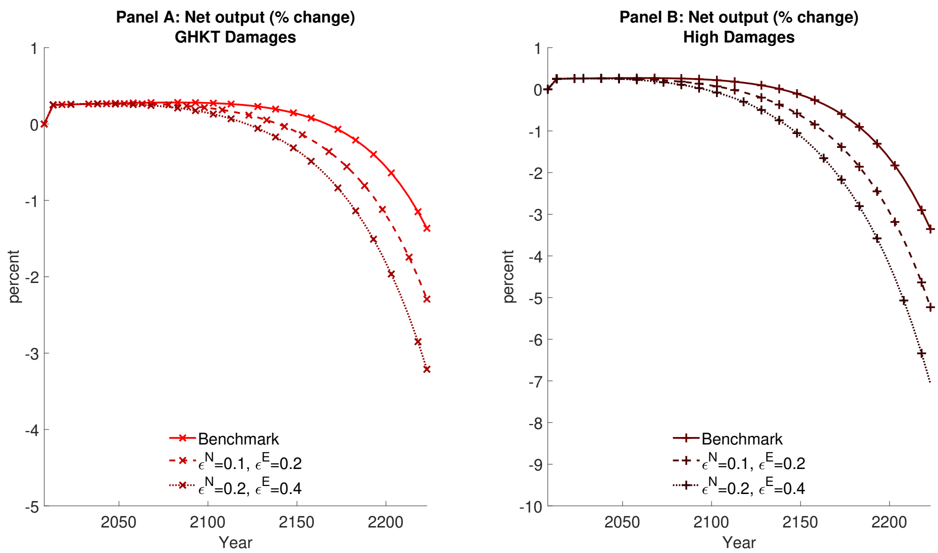
We capture these effects in a stylized manner by assuming that both US and ROW non-electricity pollution flows ($\overline{P_t^{N.Elec}}$) and ROW electricity emissions ($\overline{P_t^{ROW,Elec}}$) respond to changes in US electricity emissions ($\%\Delta P_t^{US,Elec}$) based on response elasticities ϵ^N and ϵ^E, respectively. That is, global emissions at time t are given by:

$$P_t^{Global} = P_t^{US,Elec} + \overline{P_t^{ROW,Elec}} \cdot (1 + \%\Delta P_t^{US,Elec} \cdot \epsilon^E) + \overline{P_t^{N.Elec}} \cdot (1 + \%\Delta P_t^{US,Elec} \cdot \epsilon^N)$$

where upper bars denote business-as-usual emissions levels, $P_t^{US,Elec}$ denotes endogenous US emissions as defined in (16), and where $\%\Delta P_t^{US,Elec}$ is formally defined as the percent change in US electricity emissions at time t due to the shale gas boom.

Figure A.5 compares the benchmark model results (where $\epsilon^N = \epsilon^E = 0$) with two alternate specifications, focusing on US GDP impacts of the shale gas boom in the "BAU, no IRA" scenario. Allowing for spillover effects increases the projected effects of the shale gas boom. While both the initial output benefit of the boom and the longer-term negative effects are strengthened by spillovers, the impact on the latter is larger. Intuitively, this asymmetry is driven by the facts that (i) initial output benefits are largely due to cheaper energy prices, which are invariant to emissions spillovers, and (ii) the relative importance of ROW emissions for climate change increases significantly over time. That is, due to the projected future rise of emissions from countries such as China and India, the climate benefits of reducing ROW emissions by 1% today are much smaller than the climate damages of increasing ROW damages by 1% in the year 2100. Overall, the results thus suggest that abstracting from spillovers from US electricity to other sources of emissions in the benchmark is conservative in that it will lead us to understate the overall effects of the shale gas boom.

Figure A.5—Effect of the shale gas boom on GDP in the Presence of Emissions Spillovers



Note: This figure shows the effect of the shale gas boom on net output **(in the BAU scenario without the IRA)** when there are spillovers from technological development in the US electricity sector to non-electricity US and global emissions. The boom has a more detrimental long-run effect to net output in the presence of spillovers.

A.8.2 Slow Progress in Extraction Technologies

Here we present results from a revised version of the benchmark model with slow progress in extraction technologies (B_{ct} and B_{st}). We specifically consider the limiting case with zero progress after the shale gas boom and focus on the BAU scenario without the IRA. Figure A.6 shows the results, mirroring Figure 3 for the baseline case. In line with Proposition 7, the shale gas boom (i) delays the transition to a green economy (Panel A), (ii) increases CO_2 emissions in the long run (Panel B), and (iii) decreases output in the long run (Panel C).

A.9 Extended Model

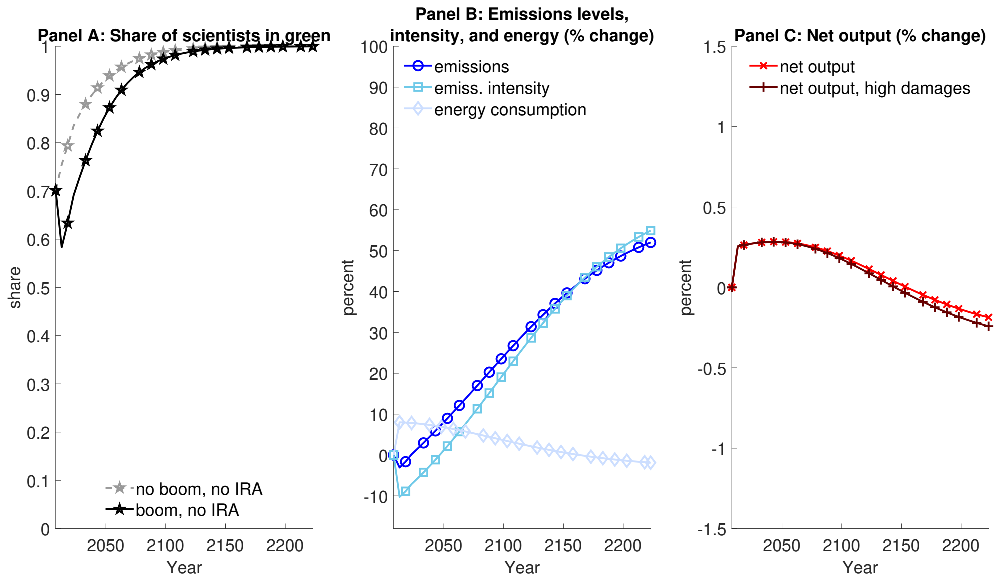
We now analyze the extended model presented in Section 5.2. First, we present the static equilibrium conditions. We then solve for the dynamic equilibrium and subsequently discuss the calibration of the model and present quantitative results.

A.9.1 Static Equilibrium and Short-Run Effect in the Extended Model

We now derive the static equilibrium conditions of the extended model. We define the fossil-fuel energy composite as

$$E_{f,t} \equiv \left(\kappa_c E_{c,t}^{\frac{\sigma-1}{\sigma}} + \kappa_s E_{s,t}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{A-18}$$

Figure A.6—Shale Boom Impacts Absent Technological Progress in Extraction Technologies



Note: This figure shows the dynamic effects of the shale gas boom in **a BAU scenario without the IRA** when there is no progress in extraction technologies (except for the boom). Panel A shows the allocation of scientists with and without the shale gas boom. While a green transition occurs in both cases, the boom significantly slows it down. Panel B shows the changes (in %) in emission intensity, energy consumption and emissions that result from the boom. As in the baseline case, the boom is associated with an initial decline in emission intensity that is reversed over time, and an increase in long-run emissions. Panel C shows the effects on net output of the boom for two calibrations of the damage function. The boom eventually decreases net output.

To find the demand for coal and natural gas energy, we solve for the maximization problem of a fossil-fuel energy composite producer:

$$\max_{E_{st},E_{ct}} p_{ft}E_{ft} - (1+\widetilde{\tau}_s)p_{st}E_{st} - (1+\widetilde{\tau}_c)p_{ct}E_{ct},$$

where $\widetilde{\tau}_i$ denotes the add-valorem tax on energy i. Using that the energy prices are still given by $p_{it} = \gamma w_t / C_{it}$, for $i = c, g, s$, we get:

$$\begin{aligned} E_{c,t} &= \kappa_c^{\sigma}\left(\frac{C_{ct}}{(1+\widetilde{\tau}_c)C_{ft}}\right)^{\sigma} E_{ft} \text{ and } E_{s,t} = \kappa_s^{\sigma}\left(\frac{C_{st}}{(1+\widetilde{\tau}_s)C_{ft}}\right)^{\sigma} E_{ft}, \qquad \text{(A-19)} \\ \text{with } C_{ft} &\equiv \left(\kappa_c^{\sigma}\left(\frac{C_{ct}}{1+\widetilde{\tau}_c}\right)^{\sigma-1} + \kappa_s^{\sigma}\left(\frac{C_{st}}{1+\widetilde{\tau}_s}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}. \end{aligned}$$

C_{ft} is the fossil-fuel aggregate productivity and the fossil-fuel aggregate price is:

$$p_{ft} = \gamma w_t / C_{ft}. \qquad \text{(A-20)}$$

Profit maximization by the electricity producer then leads to

$$E_{f,t} = \left(\frac{C_{ft}}{C_{Et}}\right)^{\varepsilon} E_t \text{ and } E_{g,t} = \kappa_g^{\varepsilon}\left(\frac{C_{gt}}{\left(1+\widetilde{\tau}_g\right)C_{Et}}\right)^{\varepsilon} E_t \quad \text{(A-21)}$$

$$\text{with } C_{Et} \equiv \left(C_{ft}^{\varepsilon-1} + \kappa_g^{\varepsilon}\left(\frac{A_{gt}}{1+\widetilde{\tau}_g}\right)^{\varepsilon-1}\right)^{\frac{1}{\varepsilon-1}}. \quad \text{(A-22)}$$

C_{Et} is still the aggregate productivity in energy and the energy price obeys (14). For given E_t, the production of the different energy inputs is given by (A-21) and (A-19).

To solve for E_t, we follow steps similar to those in the baseline model. Using that $E_{it} = C_{it}L_{it}$ for $i = c, s$ in (A-19), we get that

$$L_{ct} = \frac{\kappa_c^{\sigma}\left(1+\widetilde{\tau}_c\right)^{-\sigma} C_{ct}^{\sigma-1} L_{ft}}{\kappa_c^{\sigma}\left(1+\widetilde{\tau}_c\right)^{-\sigma} C_{ct}^{\sigma-1} + \kappa_s^{\sigma}\left(1+\widetilde{\tau}_s\right)^{-\sigma} C_{st}^{\sigma-1}} \text{ and } L_{st} = \frac{\kappa_s^{\sigma}\left(1+\widetilde{\tau}_s\right)^{-\sigma} C_{st}^{\sigma-1} L_{ft}}{\kappa_c^{\sigma}\left(1+\widetilde{\tau}_c\right)^{-\sigma} C_{ct}^{\sigma-1} + \kappa_s^{\sigma}\left(1+\widetilde{\tau}_s\right)^{-\sigma} C_{st}^{\sigma-1}}. \quad \text{(A-23)}$$

Therefore, from (A-18), we get that $E_{ft} = \widetilde{C}_{ft} L_{ft}$ with $\widetilde{C}_{ft}$ defined as:

$$\widetilde{C}_{ft} \equiv C_{ft}^{\sigma}\left[\kappa_c^{\sigma}\left(1+\widetilde{\tau}_c\right)^{-\sigma} C_{ct}^{\sigma-1} + \kappa_s^{\sigma}\left(1+\widetilde{\tau}_s\right)^{-\sigma} C_{st}^{\sigma-1}\right]^{-1}, \quad \text{(A-24)}$$

Similarly, using this expression with $E_{gt} = C_{gt}L_{gt}$ in (A-21), we get:

$$\frac{L_{ft}}{L_{gt}} = \frac{C_{ft}^{\varepsilon}\widetilde{C}_{ft}^{-1}}{\kappa_g^{\varepsilon}\left(1+\widetilde{\tau}_g\right)^{-\varepsilon} C_{gt}^{\varepsilon-1}}.$$

We can then write $E_t = \widetilde{C}_{Et} L_{Et}$ with $\widetilde{C}_{Et}$ now defined by:

$$\widetilde{C}_{Et} \equiv C_{Et}^{\varepsilon}\left[C_{ft}^{\varepsilon}\widetilde{C}_{ft}^{-1} + \kappa_g^{\varepsilon}\left(1+\widetilde{\tau}_g\right)^{-\varepsilon} A_{gt}^{\varepsilon-1}\right]^{-1}. \quad \text{(A-25)}$$

With these updated definitions of C_{Et} and $\widetilde{C}_{Et}$, L_{Et} is still given by (A-10).

To derive emissions, we use (A-19) and (A-21), and we obtain $P_t = \xi_{Et}E_t$ with the emission rate ξ_{Et} now given by:

$$\xi_{Et} = \left(\xi_c\kappa_c^{\sigma}\left(\frac{C_{ct}}{\left(1+\widetilde{\tau}_c\right)C_{ft}}\right)^{\sigma} + \xi_s\kappa_s^{\sigma}\left(\frac{C_{st}}{\left(1+\widetilde{\tau}_s\right)C_{ft}}\right)^{\sigma}\right)\left(\frac{C_{ft}}{C_{Et}}\right)^{\varepsilon}.$$

The short-run impact of the natural gas boom on the emission rate can now be written as

$$\frac{\partial \ln \xi_{Et}}{\partial \ln B_{st}} = \frac{C_{st}}{B_{st}}\left[\sigma \frac{P_{st}}{P_t} - (\sigma - \varepsilon)\,\theta_{sft} - \varepsilon\Theta_{st}\right]. \tag{A-26}$$

Here θ_{sft} is the revenue share of the gas industry within the fossil-fuel energy subsector. This expression is more likely to be negative when the within fossil-fuel substitution elasticity σ is large compared to the substitution elasticity between fossil fuel and green energy ε. The short-run effect of the natural gas boom on emissions can again be decomposed into this substitution effect which affects the emission rate ξ_{Et} and a scale effect which affects energy demand E_t.

Proposition A.5 *A natural gas boom (that is a one time increase in B_s at time $t = 0$) leads to a change in the emission rate given by (A-26). Emissions decrease in the short-run provided that natural gas is sufficiently clean compared to coal (for ξ_s/ξ_c small enough) and the ad-valorem taxes ($\widetilde{\tau}_c$, $\widetilde{\tau}_s$ and $\widetilde{\tau}_g$) are small.*

A.9.2 Dynamic Equilibrium and Innovation Effect in the Extended Model

We now derive the innovation allocation. We assume that in any period, there is always at most one innovation for a given intermediate. To maintain the assumption that fossil-fuel and green technologies can grow at the same rate, we need to consider different values for the research productivity in coal, gas, and green technology. We denote η_g research productivity in green technologies and by η_f research productivity in each of the fossil-fuel technologies. The innovation process described in Section 5.2 then leads to laws of motion for the power plant technologies given by

$$A_{ct} = \gamma^{\eta_f\left(s_{ct}^{1-\psi} + \chi s_{st}^{1-\psi}\right)} A_{c(t-1)},\ A_{st} = \gamma^{\eta_f\left(\chi s_{ct}^{1-\psi} + s_{st}^{1-\psi}\right)} A_{s(t-1)} \text{ and } A_{gt} = \gamma^{\eta_g s_g^{1-\psi}} A_{g(t-1)}, \tag{A-27}$$

with s_{ct} (resp. s_{st}) the share of scientists in coal (resp. natural gas) research.

Expected profits from clean research still obey (19) but with η_g instead of η. Instead of (20), expected profits from an innovation in fossil-fuel technologies are now given by

$$\Pi_{ct} = \eta_f s_{ct}^{-\psi}\left(1 - \frac{1}{\gamma}\right)\left(\frac{C_{ct}\left(1+\overline{\Lambda}_c\right)}{A_{ct}} p_{ct}E_{ct} + \chi \frac{C_{st}\left(1+\overline{\Lambda}_s\right)}{A_{st}} p_{st}E_{st}\right), \tag{A-28}$$

for an innovation directed at the coal technologies and by

$$\Pi_{st} = \eta_f s_{st}^{-\psi}\left(1-\frac{1}{\gamma}\right)\left(\chi \frac{C_{ct}\left(1+\overline{\Lambda}_c\right)}{A_{ct}} p_{ct}E_{ct} + \frac{C_{st}\left(1+\overline{\Lambda}_s\right)}{A_{st}} p_{st}E_{st}\right), \tag{A-29}$$

for an innovation directed at natural gas technologies.

In equilibrium, scientists are indifferent between innovating in the three sectors; therefore, denoting by q_j a R&D subsidy for sector j, we get

$$\frac{\Pi_{ct}}{1-q_c} = \frac{\Pi_{st}}{1-q_s} \text{ and } \frac{\Pi_{ct}}{1-q_c} + \frac{\Pi_{st}}{1-q_s} = 2\frac{\Pi_{gt}}{1-q_g}. \tag{A-30}$$

Using (A-19) and (A-21), we get the revenue shares within the energy sector:

$$\Theta_{gt} = \frac{p_{gt}E_{gt}}{p_{Et}E_t} = \frac{\kappa_g^{\varepsilon}}{\left(1+\tilde{\tau}_g\right)^{\varepsilon}}\left(\frac{C_{gt}}{C_{Et}}\right)^{\varepsilon-1} \text{ and } \Theta_{it} = \frac{p_{it}E_{it}}{p_{Et}E_t} = \frac{\kappa_i^{\sigma}}{(1+\tilde{\tau}_i)^{\sigma}}\left(\frac{C_{it}}{C_{ft}}\right)^{\sigma-1}\left(\frac{C_{ft}}{C_{Et}}\right)^{\varepsilon-1} \text{ for } i \in \{c,s\}. \tag{A-31}$$

Using (A-31), (A-28), and (A-29) allows us to rewrite the indifference condition for innovation within the fossil-fuel sector (in A-30) as:

$$\left(\frac{s_{ct}}{s_{st}}\right)^{\psi} = \frac{(1-q_s)\left(\frac{\kappa_c^{\sigma}}{(1+\tilde{\tau}_c)^{\sigma}}\frac{(1+\overline{\Lambda}_c)C_{ct}^{\sigma}}{A_{ct}} + \chi\frac{\kappa_s^{\sigma}}{(1+\tilde{\tau}_s)^{\sigma}}\frac{(1+\overline{\Lambda}_s)C_{st}^{\sigma}}{A_{st}}\right)}{(1-q_c)\left(\chi\frac{\kappa_c^{\sigma}}{(1+\tilde{\tau}_c)^{\sigma}}\frac{(1+\overline{\Lambda}_c)C_{ct}^{\sigma}}{A_{ct}} + \frac{\kappa_s^{\sigma}}{(1+\tilde{\tau}_s)^{\sigma}}\frac{(1+\overline{\Lambda}_s)C_{st}^{\sigma}}{A_{st}}\right)}. \tag{A-32}$$

Using the same equations together with (19) and (A-31), we can rewrite the indifference condition for innovation between the green and the fossil-fuel sector (in A-30) as:

$$\frac{\eta_f C_{ft}^{\varepsilon-\sigma}\left[\left(\frac{s_{ct}^{-\psi}}{1-q_c} + \frac{\chi s_{st}^{-\psi}}{1-q_s}\right)\frac{\kappa_c^{\sigma}}{(1+\tilde{\tau}_c)^{\sigma}}\frac{(1+\overline{\Lambda}_c)C_{ct}^{\sigma}}{A_{ct}} + \left(\frac{\chi s_{ct}^{-\psi}}{1-q_c} + \frac{s_{st}^{-\psi}}{1-q_s}\right)\frac{\kappa_s^{\sigma}}{(1+\tilde{\tau}_s)^{\sigma}}\frac{(1+\overline{\Lambda}_s)C_{st}^{\sigma}}{A_{st}}\right]}{\eta_g \frac{s_{gt}^{-\psi}}{1-q_g}\frac{\kappa_g^{\varepsilon}}{\left(1+\tilde{\tau}_g\right)^{\varepsilon}}C_{gt}^{\varepsilon-1}} = 2. \tag{A-33}$$

Finally, the scientists market clearing equilibrium condition is now given by

$$s_{ct} + s_{st} + s_{gt} = 1. \tag{A-34}$$

We then define a dynamic equilibrium of this economy.

Definition A-1 *The dynamic equilibrium is defined by the indifference conditions (A-32) and (A-33), the scientist market clearing condition (A-34), the laws of motion for A_j and the* *definitions of C_{ft}, C_{st} and C_{ct} and the laws of motion for A_{jt} (A-27).*

We note that the equilibrium is unique for sufficiently small innovation size $\ln\gamma$ (proof in Supplementary Material Appendix B.3.2).

As in the baseline model, without enough technological progress in extraction technology, innovation must occur in clean technologies in the long-run; whereas there is path dependence in innovation if there is sufficiently fast progress in extraction technology. When the extraction technologies grow at the rate $\gamma^{\eta_f\left(1+\chi^{\frac{1}{\psi}}\right)^{\psi}}-1$, and innovation occurs only in the fossil-fuel sector in the long-run, then the energy productivity variables C_{Et} and $\widetilde{C}_{Et}$ grow asymptotically at most at the same rate — which is achieved if $q_c = q_s$, see proof in Supplemental Material Appendix B.3.2. Similarly, if innovation occurs only in the green sector in the long-run, then energy productivity asymptotically grows at the rate $\gamma^{\eta_g}-1$. In the calibration, we impose $\eta_g = \eta_f\left(1+\chi^{\frac{1}{\psi}}\right)^{\psi}$, which ensures that the long-run growth potential for output gross of climate damages is the same on a clean path and on a fossil-fuel path.

We now look at the effect of the natural gas boom on innovation allocation at $t=1$. We assume that $\ln\gamma$ is low, so that we ignore the dependence of A_{ct}, A_{st} and A_{gt} on the innovation allocation at time t. For simplicity, we focus on two cases where we can derive analytical results: (1) when the elasticity of substitution between green and fossil fuels is not much lower than that between fossil fuels, $\sigma\approx\varepsilon$, which corresponds to our calibration; and (2) when most fossil-fuel innovations are common to coal and natural gas ($\chi\approx 1$). We show in Supplementary Material Appendix B.3.3, the following proposition.

Proposition A.6 *Suppose $\ln\gamma$ is small (which ensures that the equilibrium is unique).*

1. Assume that $\sigma\approx\varepsilon$. Then, a natural gas boom increases innovation in natural gas technology and decreases innovation in green technology. The effect on coal technology is ambiguous: positive for χ sufficiently close to 1, but negative for χ sufficiently close to 0.

2. Assume that $\chi\approx 1$ and $\frac{(1+\overline{\Lambda}_s)C_{st}}{(1+\widetilde{\tau}_s)A_{st}} \geq \frac{(1+\overline{\Lambda}_c)C_{ct}}{(1+\widetilde{\tau}_c)A_{ct}}$. Then, a natural gas boom leads to a decrease in green innovation and an increase in both types of fossil-fuel innovations.

In this extension, a shale gas boom need not necessarily be associated with a decline in green innovation. The reason is that when $\sigma>\varepsilon$, green technologies are more complementary to natural gas technologies than coal technologies are. As a result, a natural gas boom could potentially encourage green innovation. Clearly, this channel is dominated if σ is sufficiently close to ε. Even if σ is large relative to ε, this channel could be dominated when most fossil-fuel innovations are mostly common to coal and natural gas (χ is large) and $\frac{(1+\overline{\Lambda}_s)C_{st}}{(1+\widetilde{\tau}_s)A_{st}} \geq \frac{(1+\overline{\Lambda}_c)C_{ct}}{(1+\widetilde{\tau}_c)A_{ct}}$, which means that the "adjusted" productivity of the power plant technology relative to the extraction technology is not too large in the natural gas sector relative to coal sector. In the calibration, σ turns out to be close to ε and the natural gas boom leads to a reduction in green innovation, as in our main analysis. Finally, we remark that when $\chi \neq 1$, the effect of the natural boom on coal-based innovation is ambiguous: for χ small, the natural gas boom may relocate innovation away from coal.

A.9.3 Calibration of the Extended Model

The calibration of the extended model follows similar steps as the benchmark, with appropriate modifications and additions. First, we retain the same parameters from the literature as in Table 4 (i.e., ε, λ, ν, γ, $\xi_{c,}$ and ξ_s), and set $\sigma = 2$ as described in Section 5.2. Second, we solve for the energy share parameters $\kappa_{c,}$ $\kappa_{s,}$ and κ_g in (26) jointly with the initial fossil price index p_{ft} and quantity E_{ft} via (A-18), $1 = \kappa_c + \kappa + \kappa_g$ and the modified set of equations:

$$\frac{E_{c,t}}{E_{s.t}} = \left(\frac{\kappa_c}{\kappa_s}\frac{(1+\tau_{st})p_{st}}{(1+\tau_{ct})p_{ct}}\right)^{\sigma} \text{ and } \frac{E_{g,t}}{E_{f.t}} = \left(\kappa_g \frac{p_{ft}}{(1+\tau_g)p_{gt}}\right)^{\varepsilon}, \tag{A-35}$$

$$p_{ft} = (\kappa_c^{\sigma}(p_{ct}(1+\tau_{ct}))^{(1-\sigma)} + \kappa_s^{\sigma}(p_{st}(1+\tau_{st}))^{(1-\sigma)})^{\frac{1}{1-\sigma}}.$$

The benchmark calibration implies $\kappa_c = 0.2732$, $\kappa_s = 0.3702$, $\kappa_g = 0.3565$, $p_{f0} = 267.39$, and $E_{f0} = 2.5329$. Next, we compute the initial energy price index by extending (A-13) to

$$p_{E0} = \left(\kappa_g^{\varepsilon}\left[p_{g0}(1+\tau_g)\right]^{1-\varepsilon} + p_{f0}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}},$$

the initial energy aggregate E_0 via (A-14), and the productivity parameter $\widetilde{A_E}$ via (A-15).

Analogous to the benchmark, we then solve for the remaining unknown variables in initial equilibrium ($A_{g0}, A_{c0}, A_{s0}, B_{c0}, B_{s0}, C_{c0}, C_{s0}, C_{f0}, C_{E0}, \widetilde{C}_{f0}, \widetilde{C}_{E0}, A_{P0}, L_{E0}, L_{P0}, w_0$) in an extended version of (A-16) with 15 equations:[12]

$$Y_0 \quad = \quad (1-D(S_0))\left((1-\nu)(A_{P0}L_{P0})^{\frac{\lambda-1}{\lambda}} + \nu\left(\widetilde{A}_{E0}E_0\right)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}$$

[12]In the benchmark calibration, the results imply that $A_{g,0} = 100.3$, $A_{c,0} = 462.1$, $A_{s,0} = 450$, $B_{c,0} = 337.4$, $B_{s,0} = 119.5$, $C_{c,0} = 187.4$, $C_{s,0} = 94.4$, $C_{f,0} = 26.9$, $C_{E,0} = 42.2$, $\widetilde{C}_{f,0} = 26.9$, $\widetilde{C}_{E,0} = 41.7$, $A_{P,0} = 4.802e+03$, $\widetilde{A}_{E0} = 1.44e+05$, $L_{E,0} = 0.1382$, $L_{P,0} = 9.8618$, $w_0 = 6.87e+03$.

$$
\begin{aligned}
A_{g0} &= \frac{\gamma w_0}{p^q_{g0}}, A_{c0} = \frac{\gamma w_0}{p^q_{c0}}, A_{s0} = \frac{\gamma w_0}{p^q_{s0}}, B_{c0} = \frac{\gamma w_0}{p^r_{c0}} and B_{s0} = \frac{\gamma w_0}{p^r_{s0}} \\
C_{c0} &= \left(\frac{1+\overline{\Lambda}_c}{A_{c0}} + \frac{1}{B_{c0}}\right)^{-1} \text{ and } C_{s0} = \left(\frac{1+\overline{\Lambda}_s}{A_{s0}} + \frac{1}{B_{s0}}\right)^{-1} \\
C_{f0} &= \left(\kappa_c^{\sigma}\left(\frac{C_{c0}}{1+\tau_c}\right)^{\sigma-1} + \kappa_s^{\sigma}\left(\frac{C_{s0}}{1+\tau_s}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \text{ and } \widetilde{C}_{f0} = \frac{C^{\sigma}_{f,0}}{\frac{\kappa_c^{\sigma} C_{ct}^{\sigma-1}}{(1+\tau_{ct})^{\sigma}} + \frac{\kappa_s^{\sigma} C_{st}^{\sigma-1}}{(1+\tau_{st})^{\sigma}}} \\
E_0 &= \widetilde{C}_{E0} L_{E0} \text{ with } C_{E0} = \left(\frac{\kappa_g^{\varepsilon} A_{g0}^{\varepsilon-1}}{\left(1+\tau_g\right)^{\varepsilon-1}} + C_{f0}^{\varepsilon-1}\right)^{\frac{1}{\varepsilon-1}} \text{ and } \widetilde{C}_{Et} = \frac{C^{\varepsilon}_{E,0}}{\frac{C^{\varepsilon}_{ft}}{\widetilde{C}_{ft}} + \frac{\kappa_g^{\varepsilon} A_{gt}^{\varepsilon-1}}{\left(1+\tau_{gt}\right)^{\varepsilon}}} \\
\frac{\gamma w_0}{A_{P0}} &= (1-\nu)(1-D(S(t)))^{\frac{\lambda-1}{\lambda}} Y_0^{\frac{1}{\lambda}} (A_{P,0} L_{P,0})^{\frac{-1}{\lambda}} \text{ with } L_{P0} = L_0 - L_{E0}.
\end{aligned}
$$

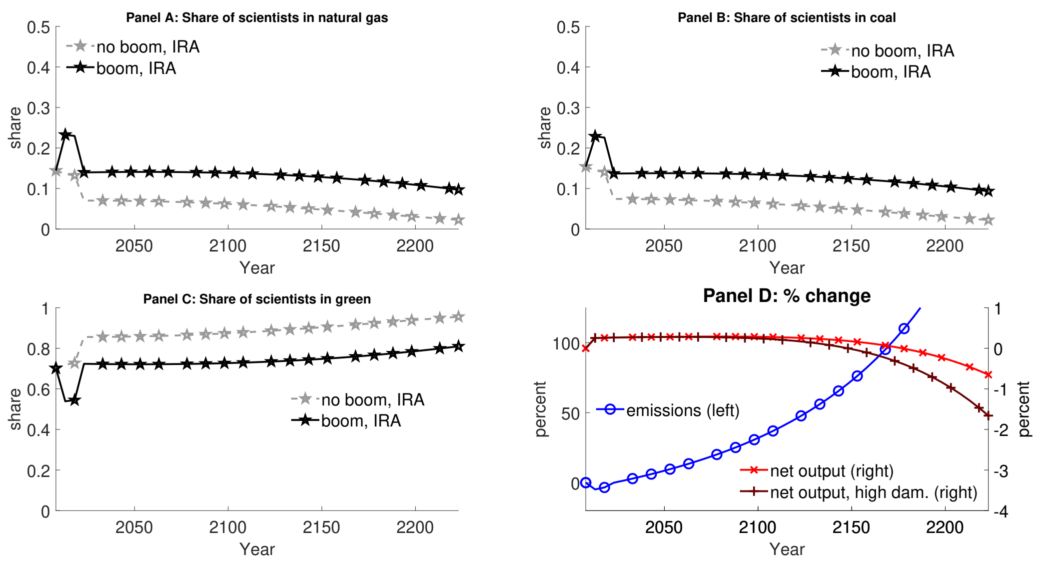
As in the baseline model, we set research productivities, the η's, to permit balanced long-run growth at 2% per year. This now implies: $\eta_g = 5 \ln 1.02 / \ln \gamma = 1.4634$ for green and an adjusted value of $\eta_f = \eta_g \left(1 + \chi^{\frac{1}{\psi}}\right)^{-\psi} = 1.077$ for fossil innovation. The remainder of the parameters are as in the baseline model.

A.9.4 Quantitative Results

First, we note that the predicted short-run effects of the shale gas boom in the extended model are similar to the baseline results in Table 5 with a -13.3% change in emissions intensity ($\%\Delta\xi_E$), a 8.1% increase in electricity demand ($\%\Delta E$), and an overall -6.3% decline in emissions ($\%\Delta CO_2$). The slightly larger decline in emissions reflects the higher elasticity of substitution between coal and natural gas in the extended model.

Second, Figure 7 in the text shows the predicted long-run impacts of the shale gas boom in the extended model. Figures A.7 and A.8 show the impacts of the shale gas boom in the extended model (i) with the IRA and (ii) without the IRA but with spillovers between coal and natural gas innovations set close to zero ($\chi = 0.01$). Both scenarii imply that, though the US economy remains on a path towards the green transition, a shale gas boom substantially delays this process, leading to long-run emissions increases and declines in net output. The latter result also speaks to the relevance of spillovers between gas and coal innovations for the results (in particular with low spillovers, innovation in coal technologies does not increase). Importantly, however, the extended model still predicts that, absent a permanent IRA, the shale gas boom permanently delays the green transition for any spillover parameter at or above $\chi = 0.31$. Empirically, as noted above, many technologies are shared between gas and coal power plants (see discussion in Lanzi et al., 2011).

Figure A.7—Shale Gas Boom Impacts in Extended Model with IRA



Note: This figure shows the dynamic effects of the shale gas boom in a BAU scenario with the IRA. Panels A, B, and C show the allocation of scientists to natural gas, coal, and green with and without the shale gas boom, respectively. While a green transition occurs in both cases, the boom significantly slows it down. Panel D shows the changes (in %) in emissions and net output that result from the boom. The boom is associated with an initial decline and subsequent increase in carbon emissions and reversed impacts on net output for both damage function calibrations.

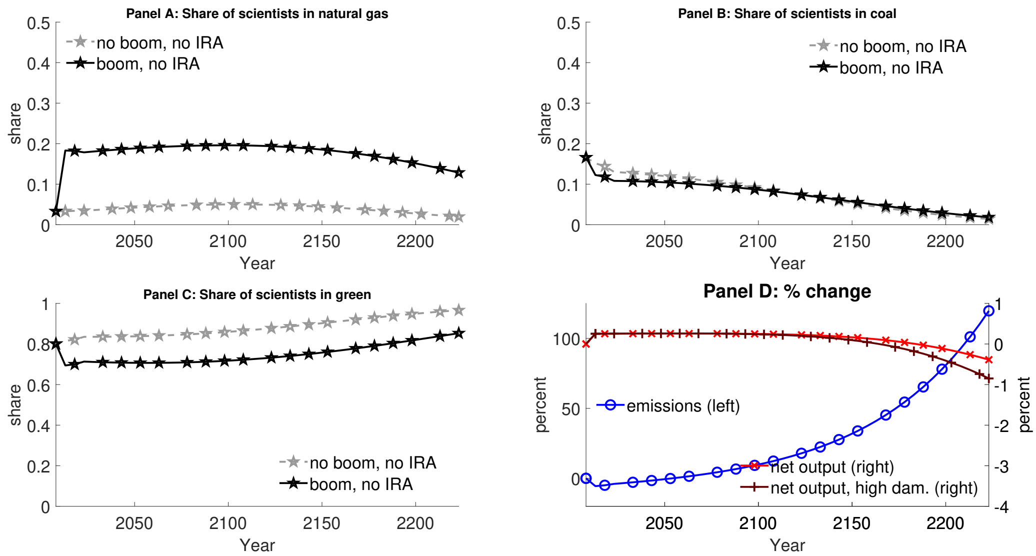
Third, we conclude by depicting welfare impacts of the boom in the extended model, again over a 400 year time horizon (Table A.2). As in the main model, the projected welfare effects of the boom with market-based discounting range from -0.4% to -2.6% in the GHKT and high damages cases with and without the IRA, respectively. Eliminating coal-gas technology spillovers mitigates these welfare effects, though they remain substantial even with a low spillover parameter around 30%.

Table A.2—Welfare effects of the Shale Gas Boom in the Extended Model

Extended Model Version	Welfare Impacts $\rho^{yr} = 1\%$		Threshold ρ^{yr}	
Damages:	GHKT	High	GHKT	High
Benchmark	-1.5%	-2.6%	2.0%	2.4%
Benchmark with IRA	-0.4%	-0.9%	1.6%	2.1%
Very low coal-gas innov. spillovers $\chi = 0.01$	-0.0%	-0.2%	1.0%	1.3%
Low coal-gas innov. spillovers $\chi = 0.31$	-0.8%	-1.5%	1.7%	2.1%

Note: This table reports, across a number of scenarios, the welfare impacts of the shale gas boom (in consumption equivalent terms), “Welfare Impacts”, and the threshold on the annual pure rate of social time preference below which these welfare impacts are negative (“Threshold ρ_{yr}”). In all cases, the welfare effects of the shale gas boom are negative for a 1% annual utility discount rate. Welfare is computed over 400 years.

Figure A.8—Shale Gas Boom Impacts in Extended Model with $\chi = 0.01$



Note: This figure shows the dynamic effects of the shale gas boom in a BAU scenario without the IRA but with coal-gas innovation spillovers set close to zero. Panels A, B, and C show the allocation of scientists to natural gas, coal, and green with and without the shale gas boom, respectively. While a green transition occurs in both cases, the boom significantly slows it down. Panel D shows the changes (in %) in emissions and net output that result from the boom. The boom is associated with an initial decline and subsequent increase in carbon emissions and reversed impacts on net output for both damage function calibrations.

Appendix References

Böhringer, C. and T. F. Rutherford (2008). "Combining Bottom-up and Top-Down". *Energy Economics* 30.2, pp. 574–596.

Chen, Y. H. H. et al. (2017). "The MIT Economic Projection and Policy Analysis (EPPA) Model: Version 5". *Joint Program Technical Note TN* 16.

Energy Information Administration (2022). *AEO Assumptions: Electricity Market Module*. URL: https://www.eia.gov/outlooks/aeo/assumptions/pdf/electricity.pdf (visited on 08/2022).

Lazard (2015). *Lazard's Levelized Cost of Energy Analysis - Version 9.0*. URL: https://www.lazard.com/media/2390/lazards-levelized-cost-of-energy-analysis-90.pdf (visited on 08/2022).

Van der Werf, E. (2008). "Production functions for climate policy modeling: An empirical analysis". *Energy economics* 30.6, pp. 2964–2979.