Induced Innovation, Inventors, and the Energy Transition*

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Abstract

We study how individual inventors respond to incentives to work on "clean" electricity technologies. Using natural gas price variation, we estimate output and entry elasticities of inventors and measure the medium-term impacts of a price increase mirroring the social cost of carbon. We find that the induced clean innovation response primarily comes from existing clean inventors. New inventors are less responsive on the margin than their average contribution to clean energy patenting would indicate. Our results strengthen the rationale for government intervention to expedite the energy transition.

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1 INTRODUCTION

Clean energy innovation is critical to reducing the costs of climate change mitigation and allowing society to avert the worst-case scenarios projected by climate scientists. A long literature in economics provides empirical evidence that innovation in clean energy responds to economic incentives, and recent research on directed technical change provides a theoretical justification for subsidizing clean technology research and development. But crafting effective subsidies requires understanding the sources and mechanisms of induced innovation.

This paper focuses on individual inventors to shed light on the origins of clean energy innovation. A vast body of research in economics underscores the pivotal role of human capital in the innovation process. However, the role of individual scientists and inventors in the energy sector has received relatively little attention from economists. What is the evolution of a typical energy inventor's career? Given the extensive training required to reach the frontier of specialized fields, are inventors likely to shift their research focus from conventional fossil fuel technologies to emerging clean technologies? What is the role of new entrants relative to incumbents? Addressing these questions is vital to understanding and influencing the pace of future clean energy innovation.

We use comprehensive global data on patent applications to characterize the careers of individual inventors working on electricity generation technologies. We extract these inventors' patent applications and classify them as either "clean," "grey," or "dirty" electricity technologies.[1] We document two new stylized facts about energy inventors. First, we find that most inventors specialize in either clean or dirty technologies. This is consistent with returns to specialization in human capital accumulation, and it raises the question of whether future government policies to encourage a shift from dirty to clean technologies may be impeded by frictions that make it difficult for individual inventors to work in different fields. Second, about half of the clean patent families in the data came from inventors who had not patented before in clean. This sizeable number highlights the crucial

1. Although emissions intensities vary significantly across different fuels and technologies, we use the simplistic terminology clean and dirty for broad categorizations in keeping with prior work (e.g., Acemoglu et al. 2012; Aghion et al. 2016). In our main definition of "clean," we include renewable and nuclear energy, while "dirty" includes patents related to the combustion of fossil fuels. "Grey" encompasses energy efficiency and biomass and waste combustion since they still emit greenhouse gases despite being cleaner than traditional fossil fuels.

role of new entrants in clean innovation.

We then study how individual inventors respond to economic incentives in order to develop a deeper understanding of the forces determining these stylized facts. Our primary measure of economic incentives is the price of natural gas, which is arguably the most important factor price in electricity markets. When natural gas is more expensive, clean technologies become relatively more competitive, and demand for them increases. Thus, if firms and inventors expect higher natural gas prices to persist, they have a greater incentive to improve clean electricity technologies.

Our empirical strategy leverages variation in natural gas prices over both countries and time to examine how inventors respond to changes in factor prices at both the intensive and the extensive margins. The residual variation in natural gas prices that we exploit stems primarily from supply shocks that are not transmitted globally due to transportation constraints. We also implement an instrumental variable strategy that isolates variation from the shale gas revolution, which shifted out the supply of natural gas and generated a persistent reduction in the price of natural gas in North America relative to other regions due to natural gas transportation constraints. This strategy mitigates concerns about the potential endogeneity of natural gas prices and the fact that inventors are likely to respond differently to transient shocks than to persistent shocks.

First, we focus on active clean inventors and estimate an intensive margin output elasticity to quantify how the number of patents an inventor produces responds to natural gas prices. We use panel data methods to model how natural gas prices affect the number of clean energy patents an inventor produces, including inventor and time fixed effects to account for cross-sectional differences as well as common shocks to innovation incentives. To do so, we first construct prices using information on the firms that individual inventors patent with. This leverages the role of firms, which effectively act as intermediaries that observe market signals and respond by organizing and directing inventors' research activities.

Second, we examine the extent to which economic incentives induce new inventors to enter clean patenting. We estimate an extensive margin elasticity, which we refer to as an entry elasticity, to quantify how the number of inventors entering clean technology responds to natural gas prices.

To do so, we shift our analysis to the firm level. We assemble a panel of firms patenting in clean energy and identify inventors listed on a firm's patents in a given year. Within those, we focus on inventors who are filing their first clean patent. We use inventors' patenting history to classify them as either: having never patented before; having patented outside of energy; or having patented in grey or dirty but not clean technologies. We count the number of inventors in each group and then estimate the elasticity of the number of new clean technology inventors with respect to natural gas prices for each group.

Together, these empirical strategies allow us to characterize how inventors respond along both the intensive and extensive margins and to compare the magnitudes of the responses. At the intensive margin, we find that a 10% increase in natural gas prices induces about 5% more clean families for the average clean incumbent. The direction and magnitude of this effect are consistent with prior work at the firm and technology levels. The instrumented elasticity estimates are similar to the non-instrumented estimates. At the extensive margin, we find that a 10% increase in natural gas prices leads to an increase in entry of up to 6% depending on the time horizon and type of entrant.

We combine these econometric estimates to study the potential effects of an increase in natural gas prices equivalent to a social cost of carbon of $51 per metric ton of carbon dioxide. We find that total clean patenting would increase roughly one-third relative to baseline patenting rates in the medium run. The dominant mechanisms of this aggregate response are increased patenting by existing clean inventors and, to a lesser extent, patenting by new entrants who had not previously produced patents.

Overall, these findings show that induced innovation in the medium run relies primarily on the intensive margin, and that the entry of new inventors plays a more minor role. We interpret this as a manifestation of path dependency, which is a key feature shaping the dynamics of directed technical change (e.g., Acemoglu et al. 2012; Aghion et al. 2016), and which provides a rationale for rapid government intervention to direct innovation toward clean technology to correct the carbon externality. Our results, therefore, reinforce this rationale for interventions to hasten the energy transition. Our findings also underscore the need for research to better understand what motivates individuals to become clean inventors.

This paper provides new empirical evidence to the literature on the economics of energy and environmental innovation. Prior research has shown that the optimal climate policy combines carbon pricing and R&D subsidies to effectively redirect scientists from dirty to clean technologies (e.g., Acemoglu et al. 2012; Acemoglu et al. 2016; Fried 2018; Hart 2019; Lemoine 2020). Empirical analyses have shown that energy price increases and environmental policies induce innovation in clean technologies (e.g., Newell et al. 1999; Popp 2002; Johnstone et al. 2010; Popp and Newell 2012; Noailly and Smeets 2015; Aghion et al. 2016; Dugoua 2021; Myers and Lanahan 2022; Gerarden 2023). Such effects have been documented both at the technology and firm levels, but there is no empirical evidence on how such incentives influence the work, and especially the research direction, of individual inventors. We provide new empirical evidence on how high-skilled workers respond to incentives that can be used to guide future modeling assumptions and policy design.[2]

This paper also relates to the literature studying the role of human capital in innovation, and especially how individual inventors respond to incentives (e.g., Jones 2009, 2010; Azoulay et al. 2011; Bell et al. 2019; Agarwal and Gaule 2020; Van Reenen 2021; Akcigit et al. 2022). In particular, Azoulay et al. (2019) and Myers (2020) highlight the role of new entrants in biomedical research and find that it is costly to influence the direction of their work. We contribute to this literature by documenting similar patterns in the context of climate change mitigation technologies.

We also build on a growing literature that studies the impacts of the shale gas revolution. Much of this literature focuses on the implications of lower natural gas prices on the electricity sector and environmental outcomes in the short run (e.g., Cullen and Mansur 2017; Linn and Muehlenbachs 2018; Knittel et al. 2019; Coglianese et al. 2020).[3] We contribute to this literature by exploiting slightly different variation and studying different outcomes. Prior papers primarily use variation within the U.S. for estimation.[4] By contrast, we leverage the significant change in natural gas prices in North America relative to other regions of the world to study how fuel price changes

2. Popp et al. (2022b) argue government investments in human capital will be needed to scale low-carbon energy.

3. Hausman and Kellogg (2015) assess welfare and distributional implications for the broader economy.

4. For example, Fowlie and Reguant (2022) exploit variation in the shale revolution's effects on natural gas prices across locations and industries to simulate the effects of a domestic carbon price on U.S. manufacturing.

induce innovation by individual inventors.[5] This innovation could have transformational effects on environmental, electricity sector, and broader economic outcomes in the long run.

2 Stylized Facts About Energy Inventors

2.1 Data

Energy Patent Data. We extract electricity generation-related patent applications from the PATSTAT database (European Patent Office 2022) using specific patent classification codes.[6] These codes help us classify patents as relating to either clean, grey, or dirty technologies. Clean technologies include zero or low-carbon electricity generation technologies (i.e., solar, wind, marine, geothermal, hydro, and nuclear).[7] Dirty technologies include patents related to the combustion of fossil fuels (i.e., coal, oil, and natural gas). In grey technologies, we group patents related to improving the efficiency of combustion processes and electricity generation from biomass and waste.

We aggregate patent applications at the level of patent families, which are collections of patents that are considered to cover the same technical content and, therefore, represent the same invention. We date families by their priority year, which is the year when the earliest application within the family was filed.

Online Appendix Figure C.1 plots the number of clean, grey, and dirty patent families over time in our sample. The trends are similar to those documented previously by Popp et al. (2022a) and Acemoglu et al. (2023), with the number of clean patent families increasing rapidly over the 2000s, followed by a decline in clean patenting since 2010. By contrast, the number of new patent families

5. Acemoglu et al. (2023) present suggestive evidence of the impact of shale gas development on clean innovation as motivation for a theoretical model of the long-run consequences of the shale gas revolution.

6. We use codes from the Cooperative Patent Classification and the International Patent Classification (European Patent Office 2020, 2021), building on previous studies that have listed relevant energy codes (Johnstone et al. 2010; Lanzi et al. 2011; Dechezleprêtre et al. 2014; Popp et al. 2022a). See Online Appendix A.3 for a detailed list of codes.

7. A patent family is classified as clean if it has at least one code related to renewable or nuclear energy. We also consider an alternative definition of clean that includes some enabling technologies relevant to electricity and excludes families that include any grey or dirty codes. Results for that definition are in the appendix.

in grey and dirty technologies has been more stable over the past three decades.

Inventor Data. Next, we identify individual inventors to construct a panel dataset of their patenting activity over time. Intellectual property authorities require that all individuals who contributed to an invention be listed as inventors on the application, but they do not use unique identifiers for individual inventors. To analyze inventors' activities over their careers, researchers must, therefore, use the inventor names written on patent applications to identify unique inventors.

Our starting point is to use the PATSTAT Standardized Name identifier, which results from a harmonization procedure completed prior to data publication.[8] This harmonization, however, is incomplete: 70% of the inventors in our sample are not included. We improve the PATSTAT identifier by standardizing inventors' names and disambiguating inventors based on string matching.[9]

For our analysis, we focus on inventors who are listed on at least one energy patent application filed in an OECD country after 1990.[10] We define the year when the inventor becomes connected to a family as the earliest year when the inventor appears on any of the applications in the family. In the end, our sample contains a total of 726,049 energy inventors.

2.2 Stylized Facts

Most Energy Inventors Specialize in Clean or Dirty Technologies. Figures 1a and 1b show the extent to which energy inventors specialize in either clean, grey, or dirty patenting based on inventors' global patent portfolios between 1990 and 2019. To construct the graphs, we classify inventors with at least one energy patent family in a given year according to their last three years of patenting.

On average throughout the period, 29% of energy inventors patent in clean energy only. Inventors who patent in grey and/or dirty energy are more numerous, making up 60% of energy inventors.[11]

8. Li et al. (2014) provides disambiguated identifiers for USPTO inventors only. Our study requires disambiguation of all inventors globally.

9. Online Appendices A.2 and B explain this procedure in detail.

10. We limit our geographic scope because natural gas price data is available for OECD countries only.

11. Here, for simplicity, we restrict our attention to energy-related patents. Hence, when we say that an inventor patents only in clean, we mean that all of the energy patents the inventor produces are in clean. The inventor may also

By contrast, the share of energy inventors who are active in both clean and dirty or grey energy patenting is only 11%.

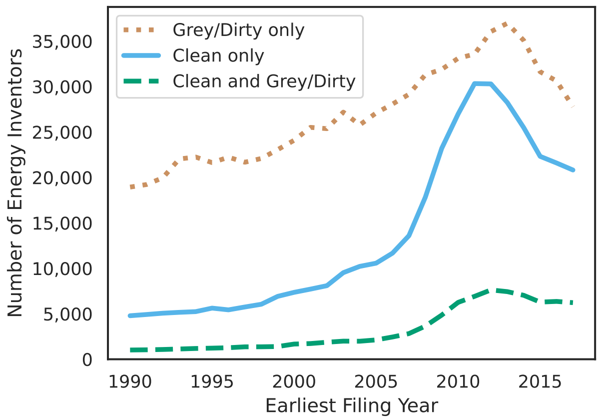
Figures 1a and 1b also show how specialization has changed over time. The total number of energy inventors increased until 2012, led by a rapid rise in the number of clean inventors during the 2000s. During that period, the share of inventors working in clean energy roughly doubled. On the other hand, the number of inventors working on dirty and/or grey energy grew more gradually over time, so that their share fell significantly over the 2000s. Finally, while the number of inventors working in both areas has increased over time, it remains small relative to the clean and dirty categories.

New Entrants are a Quantitatively Important Source of Clean Patenting To assess the contribution of different types of inventors to innovation output, we document the number of clean families produced by inventors based on their prior patenting behavior. Figures 1c and 1d summarize the distribution of clean families over the sample period. To compute these numbers, we inversely weight patent counts by the number of inventors associated with each patent family to avoid double-counting, and then aggregate patent counts across inventors of each type.

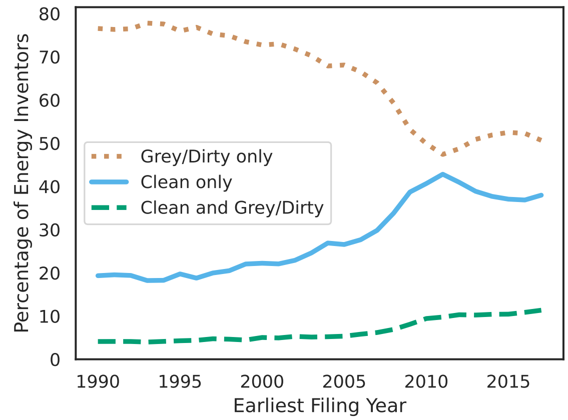
On average, throughout the period, we find that only about half of clean families (49%) are from clean incumbents, either inventors with prior patenting in clean only (32%) or in clean as well as grey and/or dirty (17%). Roughly one-third of families (28%) come from inventors who did not previously appear in the patent data. About 19% come from inventors that had previously patented in fields that we do not classify as energy. Finally, a small fraction of clean families (4%) come from inventors with prior patenting in grey and/or dirty but not clean.[12]

patent in other non-energy fields.

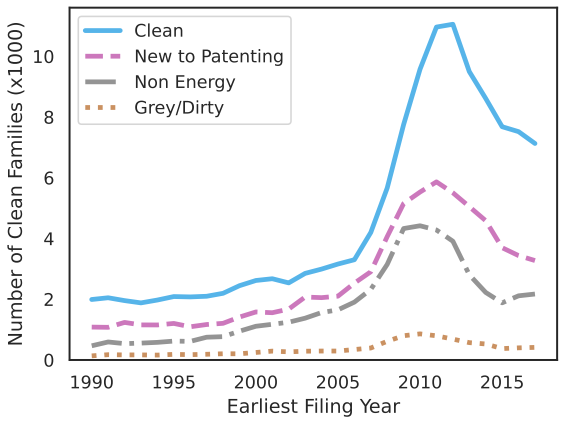
12. We find similar distributions of incumbents versus entrants for grey and dirty families (see Online Appendix C.3).



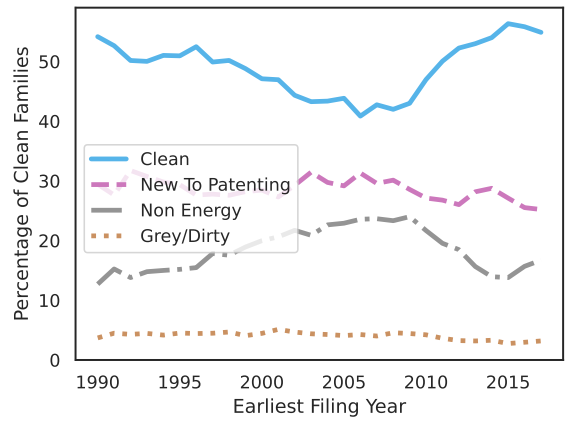
(a) Energy Inventors by Type (Levels)



(b) Energy Inventors by Type (Shares)



(c) Clean Families by Origin of Inventor (Levels)



(d) Clean Families by Origin of Inventor (Shares)

FIGURE 1

Type of Energy Inventors and Clean Patent Families

Note: Figures 1a and 1b show the extent to which energy inventors specialize in either clean, grey, or dirty patenting. We focus on inventors' global patent portfolios for inventors with at least one energy patent in an OECD country after 1990. To construct the graphs, we first identify inventors with at least one energy family filed in year t, and then classify them according to their last three years of patenting activity. This three-year window is used only for Figures 1a and 1b and not for other figures and results in the paper. Figures 1c and 1d illustrate the types of inventors behind clean families over time. They plot trends over time in the levels and shares of clean families produced by inventors with previous clean patents, inventors new to patenting, inventors with previous patents outside the set of energy technologies under study, and inventors with previous grey and/or dirty patents. Families with multiple inventors are fractionally attributed to the inventors to avoid double-counting. In our data, only 3.0% of inventors starting in grey and/or dirty eventually enter clean patenting.

3 Empirical Strategy

The remainder of the paper focuses on how innovation in clean electricity generation technologies responds to changes in economic incentives, which we proxy by changes in natural gas prices. In this section, we discuss the sources of price variation that we exploit. We then explain our approach to estimating clean innovation responses on both the intensive and extensive margins.

3.1 Identifying Variation

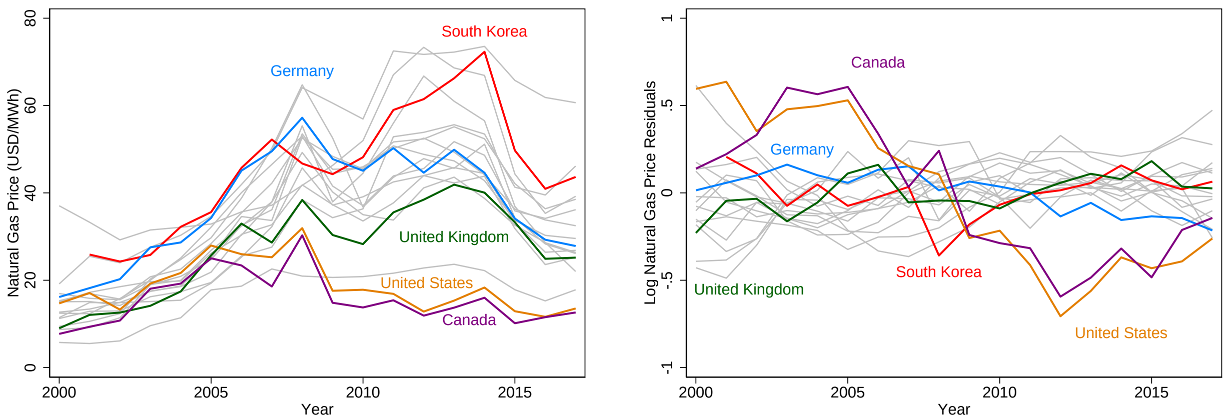
Our empirical strategy builds on a literature on induced innovation dating to Hicks (1932). Hicks hypothesized that a change in relative factor prices would spur innovation to use less of the factor which had become relatively expensive. We use natural gas prices as a proxy for relative factor prices in electricity generation, and therefore as an indirect proxy for the expected returns from innovation in renewable and nuclear electricity generation technologies that compete with natural gas-fired electricity generation.[13]

We use data on natural gas prices from the International Energy Agency (2020) and exploit variation across countries and time, visualized in Figure 2a.[14] The price variation across countries at a given point in time stems primarily from constraints on the transportation of natural gas. The clearest example of this is the shale gas revolution. The development of horizontal drilling and hydraulic fracturing caused prices for natural gas in North America to decline significantly in 2009. These price reductions were not seen in other regions for many years due to short-run capacity constraints on the export of natural gas. The identifying variation used in our primary empirical strategy comes from residual variation in natural gas prices after conditioning on country and time fixed effects, plotted in Figure 2b.

To mitigate concerns about potential endogeneity of natural gas prices due to reverse causality – that clean technology developments may affect demand for natural gas, and therefore affect natural gas prices – we also implement an instrumental variable strategy that restricts attention to the variation in natural gas prices caused by the shale gas revolution. We use a binary instrument that

13. While renewable and nuclear technologies primarily serve as substitutes to fossil fuel technologies, they can also be complements in some markets and time periods. The role of these technologies as substitutes versus complements generates opposing innovation incentives. Our empirical strategy estimates the net effect of these countervailing forces. The Online Appendix also presents results using a broader definition of clean that includes enabling technologies such as smart grid and energy storage. However, the extent to which those enabling technologies are substitutes or complements to natural gas electricity generation is less clear than for clean electricity generation technologies.

14. Natural gas prices are in nominal U.S. dollars per megawatt-hour. All econometric analysis in the paper includes time fixed effects, which absorb common time-varying factors including changes in the value of U.S. dollars due to inflation, so the results are invariant to using prices in real terms.



(a) Prices

(b) Residuals

FIGURE 2
Natural Gas Prices and Residuals across Countries and Time

Note: Panel a plots the price of natural gas in each country over time using data from the International Energy Agency (2020). Prices are in U.S. dollars per megawatt-hour (MWh). Panel b plots residuals from a regression of the natural logarithm of the natural gas prices from Panel a on country and year fixed effects.

is one for the United States and Canada starting in 2009 and is zero in all other countries and time periods. This instrument explains 51% of the residual variation in natural gas prices after accounting for country fixed effects, time fixed effects, and other control variables included in our main specifications. We use a control function approach based on Lin and Wooldridge (2019) to implement the instrumental variable strategy, detailed in Appendix E.

We use a shift-share research design to utilize this country-level identifying variation to study outcomes at the inventor and firm levels, as described in the subsequent sections. In doing so, we build upon recent methodological papers by Adão et al. (2019), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (2022). For identification we rely on exogeneity of the natural gas price shocks rather than exogeneity of the shares (i.e., weights), as in Adão et al. (2019) and Borusyak et al. (2022).[15]

15. These papers focus on linear models and provide new procedures for inference that are robust to correlated residuals among units with similar exposure shares. Unfortunately, we are not aware of analogous results for nonlinear models. Thus, we cluster regressions by unit (i.e., inventor or firm). Online Appendix F presents additional results in which we conduct estimation and inference using linear models following the methods from Borusyak et al. (2022). Those results remain statistically significant.

3.2 Response at the Intensive Margin: Output Elasticity of Incumbents

To quantify the magnitude of the induced innovation response at the intensive margin, we focus on inventors who have produced at least one clean patent and study how their clean patenting activity responds to natural gas prices. Specifically, we model patenting as a function of energy prices and inventor characteristics:

$$PAT_{it}^{C} = \exp(\beta_P \ln P_{it-1} + \beta_X X_{it-1} + \gamma_t + \eta_i) + u_{it}, \tag{1}$$

where PAT_{it}^{C} is the count of clean families filed by inventor i in year t;[16] P_{it-1} is the price of natural gas that inventor i is exposed to in year $t-1$;[17] X_{it-1} is a set of controls; γ_t and η_i denote year and inventor fixed effects; and u_{it} is an error term. In some specifications, we also include tenure fixed effects to account for how productivity evolves over the course of inventors' careers.[18] We estimate equation 1 via Poisson pseudo maximum likelihood under the assumption that natural gas prices are conditionally weakly exogenous.

Our empirical model requires a measure of the natural gas price(s) that individual inventors use to form beliefs, which we do not directly observe. Most inventors patent in conjunction with corporations, and we view their incentives as primarily mediated by firms. Thus, we construct price measures for each individual that depend upon the prices that the firm(s) they are associated with are exposed to.[19]

16. We construct inventors' time-series such that the first year corresponds to the first observed clean patent filed by the inventor, and the last year corresponds to the year of the last observed patent (of any type). Our results are robust to arbitrarily truncating inventors' time-series at 50% of their observed tenure. See Online Appendix G.4.

17. We use the previous year's prices as a proxy for individual inventors' beliefs about future prices while still allowing a lag that gives inventors time to respond to variation in price. While we do not have direct evidence on individual inventors' beliefs about natural gas prices, Anderson et al. (2013) find that U.S. consumer beliefs about gasoline prices are indistinguishable from a no-change forecast. We also estimate more flexible distributed lag models that include prices from the previous three years. This choice of lags is supported by survey evidence on inventor activities from Nagaoka and Walsh (2009), who report that the average amount of time spent on research leading up to a patent application is less than two years, and that between 80% and 90% of patents involve three or fewer years of research leading up to an application.

18. The tenure variable is the number of years since we observe an inventor's first patent (of any type).

19. Patent applications provide the names of applicants (i.e., the entities retaining the intellectual property rights), and most applicants are for-profit organizations. We connect inventors to firms based on the applicants that appear on their patents. The link between PATSTAT inventors and Orbis firms is provided by Orbis IP (Bureau van Dijk). Most inventors are linked to multiple firms, either because their individual patents are jointly filed by multiple companies

We, therefore, construct inventor-specific prices in two steps. First, we compute firm-specific prices as the weighted average of country-level prices. Second, we compute inventor-specific prices as the weighted average of firm-level prices. The resulting prices are given by

$$\ln P_{it} = \sum_j s_{ij} \sum_c \frac{s_{jc} GDP_c}{\sum_c s_{jc} GDP_c} \ln P_{ct},$$

where P_{ct} is the average tax-inclusive natural gas price in country c in year t; s_{ij} is the share of inventor i's patent families that are associated with firm j;[20] and s_{jc} captures exposure of firm j to country c. We calculate s_{jc} as firm j's share of energy patents in country c.[21] This method of constructing firm-specific prices is similar to prior analyses of induced innovation at the firm level (e.g., Noailly and Smeets 2015; Aghion et al. 2016).[22] Finally, GDP_c is the average GDP of country c from 1990 to 2018 and adjusts for differences in market size across countries.

We use the same weighting method to construct inventor-specific measures of the country-level controls contained in X_{it-1}. These variables are the natural logarithms of GDP per capita (World Bank 2020a, 2020b) and public spending on energy and low-carbon research, development, and demonstration (RD&D) (International Energy Agency 2019). These factors are included because they are likely to influence patenting, and they may be correlated with natural gas prices.

at one point in time, or because they switch between firms over time. Our results hold even when we only consider inventors who have been associated with a single firm (see Appendix G.6). Independent "garage" inventors who are not associated with any firms represent 13% of individual inventors in the data. For these inventors, we use the price of their country of residence.

20. We use observations across all years to construct these shares because 67% of inventors do not patent before 2000.

21. To mitigate concerns about the potential endogeneity of the shares, we use observations in a pre-period (1990-1999). For firms that do not apply for patents prior to 2000 (52% of firms in the sample), we assume they are equally exposed to all countries (weighted by their GDP). Our results are robust to using weights based on all-period patenting. See Online Appendix G.5 for details.

22. This approach also allows us to rely on results from the methodological literature on shift-share research designs. However, it makes the inventor-level price variable less interpretable as a price. In Appendix J, we repeat our analysis by first computing inventors' exposure-weighted prices, and then taking the natural logarithm. Our results are robust to using this alternative functional form.

3.3 Response at the Extensive Margin: Entry Elasticity of Inventors

Next, we examine whether changes in natural gas prices induce inventors who have not previously worked on clean energy technology to enter clean patenting. Because we only observe inventors once they patent and do not observe their education or career history, we are unable to use within-inventor variation in natural gas prices to study extensive margin responses. Instead, we use firm-level information on patenting portfolios and the inventors they patent with. For each firm in each year, we count the number of inventors filing clean families with the firm for the first time in their career, meaning that the inventor never patented in clean before year t.[23] We use these data to estimate a firm-level model analogous to the inventor-level model in equation 1:

$$E_{jt}^{k} = \exp(\beta_P^k \ln P_{jt-1} + \beta_X^k X_{jt-1} + \gamma_t^k + \eta_j^k) + u_{jt}^k, \tag{2}$$

where E_{jt}^{k} is the number of new entrant inventors of type k filing a clean family with firm j in year t.[24] We classify entrants into three types: those who previously patented in grey and/or dirty but not clean energy, those who previously patented outside of energy, and those who had not previously patented. $\ln P_{jt-1}$ is the exposure-weighted log price of natural gas for firm j in year $t-1$. X_{jt-1} includes the exposure-weighted logs of GDP per capita, energy, and low-carbon public RD&D spending for firm j in year $t-1$. These variables are constructed as described in Section 3.2. Year and firm fixed effects are denoted γ_t^k and η_j^k, and u_{jt}^k is an error term. We estimate these models separately by type.

23. The coverage of the correspondence between PATSTAT and Orbis is severely limited after 2014. For this reason, we restrict our firm-level sample to years between 2000 and 2014.

24. To avoid double-counting inventors who file patents with multiple firms, we weigh the relationship between a firm and an inventor by the inverse number of firms the inventor patented with in that year.

4 RESULTS

4.1 Output Elasticity Estimates

Table 1 contains estimates of the elasticity of clean patenting with respect to lagged natural gas prices. Panel A presents baseline results from models that include fixed effects and use all residual variation in natural gas prices. Panel B presents results from instrumental variable models that only use price variation from the shale gas revolution. Panel C presents results from a distributed lag model which uses all residual variation in natural gas prices in the three years prior to patenting. The columns contain alternative specifications of Equation 1.[25] The first two columns use the simple count of clean families as the outcome variable. The third and fourth columns use the count of clean families weighted by the number of citations they received.[26] The last two columns use the simple count of clean families inversely weighted by the number of coinventors associated with each family (i.e., "fractional" count).[27]

In Panel A, all six specifications yield output elasticities of around 0.45. The effect is somewhat larger when families are weighted by citations, indicating that price variation affects the production of higher-quality patents on the margin. By contrast, it is somewhat smaller when using fractional patent families, suggesting that price variation affects patenting by teams more than by individual inventors on the margin.

Panel B of Table 1 presents estimates from the instrumental variable strategy. Overall, the qualitative patterns across columns are similar to those in Panel A, though the magnitudes differ somewhat. The most likely explanation for the differences between Panels A and B is that the price variation used to identify the output elasticity is different and that the local average treatment effect of the instrument is different from the average treatment effect.[28] The shale gas revolution generated a large decline in natural gas prices in North America that was expected to persist far

25. We document results with additional outcome variables in Online Appendix G.3.

26. Specifically, for a family filed in year t, the weight is equal to the ratio of the number of citations the family received within three years over the number of citations that the average energy family filed in year t received.

27. For example, if an inventor produced one clean family in a given year in conjunction with another inventor, the outcome would be 0.5 rather than 1. We use this approach to avoid double-counting.

28. Other potential explanations for the differences include price endogeneity and sampling variation.

TABLE 1

Estimates of Incumbent Inventors' Elasticity of Patenting with Respect to Natural Gas Prices

	Count of Clean Patent Families					
	Simple Count		Citation-Weighted		Coinventor-Weighted	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline Poisson estimates						
Prices (log, t-1)	0.495	0.396	0.582	0.451	0.458	0.374
	(0.038)	(0.039)	(0.048)	(0.048)	(0.049)	(0.049)
Inventors	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
Pseudo-R2	0.291	0.292	0.373	0.375	0.265	0.266
Panel B: Instrumental variable estimates						
Prices (log, t-1)	0.523	0.308	0.871	0.596	0.412	0.211
	(0.058)	(0.060)	(0.077)	(0.077)	(0.071)	(0.072)
Inventors	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
First-stage F-statistic	163	163	163	163	163	163
Panel C: Distributed lag estimates						
Cumulative effect (3 lags)	0.534	0.420	0.551	0.410	0.564	0.441
	(0.050)	(0.052)	(0.065)	(0.066)	(0.059)	(0.062)
Inventors	80,795	80,795	80,795	80,795	80,795	80,795
Observations	572,195	572,195	572,195	572,195	572,195	572,195
Pseudo-R2	0.294	0.295	0.370	0.372	0.267	0.268
Year fixed effects	X	X	X	X	X	X
Inventor fixed effects	X	X	X	X	X	X
Tenure fixed effects		X		X		X
Country-year covariates	X	X	X	X	X	X

Note: The dependent variables are the number of clean patent families, either unweighted, weighted by citations, or inversely weighted by the number of coinventors, depending on the column. Panels A, B, and C contain estimates of the same parameters using different estimation strategies. Panel A presents estimates of equation 1 estimated via Poisson pseudo-maximum likelihood. Standard errors are clustered by inventor and reported in parentheses. Panel B presents estimates of equation E.2 estimated via the control function approach described in the text, using the shale gas revolution as an instrument for natural gas prices. Standard errors are constructed via block bootstrap of the two-step control function approach, sampling inventors 250 times with replacement. The first-stage F-statistic for the instrumental variable estimates is from estimating equation E.1 at the country-year level rather than the inventor-year level, since the instrument varies at the country level and it thus provides a more conservative assessment of the instrument's strength. Panel C is analogous to Panel A except that the models include three lags of natural gas prices and all other covariates that vary across both countries and time, and the coefficients represent cumulative effects.

into the future. This expectation of persistent price changes could have had a larger impact on the incentives for engaging in high-risk, high-reward innovation that is more likely to be cited than it had on the incentives for more incremental innovation (relative to other, potentially transient price variation).

In Panel C, we present results from a distributed lag version of the baseline Poisson model as a complementary approach to capture the medium-run effects of persistent price changes. The elasticity estimates are now quite similar across columns. Given how similar the estimates are across Panels A, B, and C, and given that a large fraction of the overall variation in the data is driven by the shale revolution, we focus on the non-instrumented results for the remainder of the paper.[29]

4.2 Entry Elasticity Estimates

Table 2 contains estimates for the entry elasticity with respect to lagged natural gas prices. Each column corresponds to a different type of entrant. Panel A presents estimates from models with one lag. Panel B presents the cumulative effect from distributed lag models with three lags. In Panel A, the estimates are positive but somewhat imprecise. The entry elasticity point estimates are similar across types of entrants. In Panel B, the estimates for new-to-patenting and grey/dirty entrants are larger and more precisely estimated. The change in magnitude is intuitive because inventors and firms may need time to respond to price changes, and because they are likely to respond less to transient than to persistent price changes. On the other hand, we do not find clear evidence that non-energy inventors respond to price shocks.

29. Appendix G also contains results for a broader definition of clean patenting that includes enabling technologies. The estimates are typically smaller in magnitude than the main estimates, which is as expected since enabling technologies are not direct substitutes for electricity generated from natural gas.

TABLE 2
Estimates of the Elasticity of Inventor Entry with Respect to Natural Gas Prices

	Number of Clean Inventors		
	New to Patenting	From Grey/Dirty	From Non-Energy
	(1)	(2)	(3)
Panel A: Baseline Poisson estimates			
Prices (log, t-1)	0.212	0.143	0.122
	(0.127)	(0.099)	(0.105)
Firms	3,822	4,970	4,930
Observations	52,982	68,709	68,223
Pseudo-R2	0.671	0.591	0.624
Panel B: Distributed lag estimates			
Cumulative effect (3 lags)	0.509	0.653	0.203
	(0.168)	(0.122)	(0.160)
Firms	3,680	4,777	4,708
Observations	43,262	55,612	55,075
Pseudo-R2	0.680	0.595	0.631
Year fixed effects	X	X	X
Firm fixed effects	X	X	X
Country-year covariates	X	X	X

Note: The dependent variables are the fractional number of inventors (that is, inversely weighted by the number of firms they are associated with) of each type within each firm who are new to patenting in clean patent families in that year. The sample used for estimation is a balanced panel of firms from 2000 to 2014. Panel A presents estimates of equation 2 estimated via Poisson pseudo-maximum likelihood. Standard errors are clustered by firm and reported in parentheses. Panel B is analogous to Panel A, except that the models include three lags of natural gas prices and all other covariates that vary across both countries and time, and the coefficients represent cumulative effects.

5 How would Carbon Pricing Induce Innovation?

To place the intensive and extensive elasticity estimates in context, we analyze the effects of a persistent natural gas price increase equivalent to the U.S. Government's social cost of carbon of $51 per metric ton of carbon dioxide. This corresponds to 54% of the GDP-weighted global average price of natural gas in 2014. We model the medium-run effects of this price increase over 10 years.

To calculate the aggregate impact of this change in natural gas prices, we use a first-order approximation that combines responses along the intensive and extensive margins. We use the estimated elasticities from the distributed lag models in Sections 4.1 and 4.2 along with data on baseline rates of patenting and entry to compute the contribution of each margin.[30] The extensive

30. To avoid double-counting, we use elasticities estimated using the count of clean families inversely weighted by the number of coinventors and the number of inventors inversely weighted by the number of firms they are associated with.

margin responses are computed separately by entrant type and take into account typical patenting rates over the first 10 years after an inventor enters clean patenting. Appendix I provides a formal description of our approach and more details on its implementation as well as its limitations.

Table 3 summarizes the results. In the medium run, intensive margin responses by incumbent inventors are the largest source of induced patenting. Within the extensive margin responses, entry to patenting by new inventors is quantitatively most important. Responses by inventors who had previously produced patents related to grey or dirty technologies are next most important. Finally, entry by inventors who had previously worked on technologies outside energy contributes a small and imprecisely estimated amount. In total, this represents a clean patenting increase of 36% relative to a scenario in which the baseline rate of clean patenting from 2014 had been constant over 10 years.

TABLE 3
Predicted Impacts of Carbon Pricing on Clean Patenting

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	37,886	66.1
	(5,326)	(5.8)
Extensive margin response		
Entry from grey/dirty	5,884	10.3
	(1,099)	(2.1)
Entry from non-energy	2,299	4.0
	(1,812)	(3.1)
Entry to patenting	11,237	19.6
	(3,709)	(5.6)
Total	57,307	100.0
	(6,828)	.

Note: Predicted changes in the number of clean patent families due to a persistent 54% increase in natural gas prices over the course of 10 years, relative to a base year of 2014. The total change in patenting represents an increase of 36% relative to baseline patenting rates. Output and entry elasticities are estimated using three lags of natural gas prices as in Panel C of Table 1 and Panel B of 2. Inputs for the extensive margin analysis are derived from a balanced panel of firms from 2000 through 2014 as in Table 2. Standard errors are constructed using the delta method.

To assess the sensitivity of these results, we present analogous estimates using alternative specifications and samples in Online Appendix I.3. While the absolute magnitudes of patenting activity depend on the specification, the relative importance of each margin does not: in all cases, the largest sources of induced patenting activity are increased patenting by incumbent inventors, followed by entry of new inventors without prior patents.

6 CONCLUSION

We draw two main conclusions from our analysis. First, inventors typically specialize, either in clean, grey, or dirty technologies. Notably, around half of the clean patents come from inventors who previously specialized in clean technology, and these inventors' output responds to changes in natural gas prices. Second, while new entrants are critical to clean innovation, they don't respond strongly to changes in natural gas prices, particularly those who have previously patented in non-energy sectors.

Our carbon pricing analysis shows that induced innovation is primarily driven by intensive margin increases in incumbents' patenting output. Extensive margin entry of new inventors plays a more minor role. These responses on the margin contrast with the roughly equal split of patenting between the two groups on average.

These findings raise the question of whether policies encouraging a shift from dirty to clean may be impeded by frictions that make it difficult for individual inventors to work in different fields and highlight the need for further work to understand better what drives individuals to become clean inventors.

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ONLINE Appendix

Induced Innovation, Inventors, and the Energy Transition

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A Data Cleaning and Construction

A.1 Overview of Patent Data Cleaning and Construction

We used the Spring 2022 Edition of PATSTAT from the European Patent Office (2022). There's a time lag between when patents are filed and when they appear in the database. As a result, data after 2019 is incomplete, with many patent applications missing.

We group patents by DOCDB simple patent families to prevent counting the same invention multiple times. Sometimes, multiple patents are filed for the same invention. This can happen if the patents have slightly different details about the same invention or if identical patents are filed in different countries.

PATSTAT provides the names and identifiers of the inventors and applicants listed on patent applications. However, only a subset of the identifiers is disambiguated. For this reason, we further process inventor names and improve inventor disambiguation (see next section for details). For applicants, we leverage Orbis Intellectual Property (Orbis IP), a database from Bureau van Dijk that contains links between private organizations and their patent applications. We match data from Orbis IP with PATSTAT using patent application numbers. In the end, this allows us to link DOCDB families in PATSTAT to BvD ids of Orbis establishments associated with these families.

Furthermore, PATSTAT provides extensive information about each patent family, especially where each application was filed. Since our data on natural gas prices only covers OECD countries, we concentrate on inventors who have submitted at least one energy patent in an OECD country. When categorizing inventors (like clean, grey/dirty, or non-energy), we consider their entire patent history in PATSTAT, no matter where the patent was filed.

A.2 Summary of Inventor Disambiguation and Cleaning

This section provides a summary of cleaning steps on inventor names. For more details, see Section B.

We standardize inventor names by starting with the PATSTAT Standard Name identifier and then removing special characters, changing all middle names to middle initials, and keeping only the first middle initial for people with multiple middle names.

We then use granted patent applications from the USPTO to compare the performance of our approach with the disambiguation effort done by Li et al. (2014). We find that for the subsample of inventors listed on USPTO patent grants between 1975 and 2010, our approach yields 92.1% of correct matches.

One concern is that our approach is susceptible to a "John Smith" problem, whereby we wrongly tag two identifiers as being the same inventor. Here, we adopt a conservative approach to limit the potential for false positives. We count the number of countries and the number of PATSTAT Standardized Name identifiers associated with each unique name that remains after our standardization procedure. For unique names for which either the number of countries or the number of PATSTAT identifiers is above the 99th percentile, we revert back to identifying unique inventors based solely on their PATSTAT identifiers. To be conservative, when inventors have patenting gaps of more than 15 years, we ignore observations before the gap. We also drop inventors whose patent history spans more than 60 years.

A.3 Clean, Grey, and Dirty Classification using Patent Technological Codes

To study the type of energy technologies in patent applications, we use the codes given on the patent filings. These codes tell us if the patent is about clean, grey, or dirty energy technologies. We use codes from both the Cooperative Patent Classification (CPC) and the International Patent Classification (IPC). This way, we can include many patent families. Specifically, we need IPC codes to include patents from China and Japan, as they don't use the CPC.

We make a list of energy codes that are relevant to electricity generation based on previous studies (Johnstone et al. 2010; Lanzi et al. 2011; Dechezleprêtre et al. 2014; Popp et al. 2022). These codes are shown in Tables A.1, A.2, and A.3. Note that we do not include codes related to fracking in "dirty" since this would introduce endogeneity with respect to changes in natural gas prices. We also do not include patents related to carbon capture and storage in "clean" since such technologies are complementary to fossil fuels.

In our main method, we say a patent family is "clean" if it has at least one code about renewable or nuclear energy. With this method, even if a patent has grey or dirty codes, it's still "clean" if it has a renewable or nuclear code.

We also use another, broader, method to define "clean." This method is different in two ways. First, it includes more than just renewables and nuclear; it also includes other enabling technologies related to electricity (see Table A.1). Second, it does not consider patents "clean" if they have any grey or dirty codes. Robustness results using this broader definition are contained throughout this Online Appendix.

A "dirty" patent family is one that has at least one "dirty" code and no "clean" or "grey" codes. "Grey" patent families are those that: 1) have at least one "grey" code, irrespective of whether they also have "clean" or "dirty" codes; or 2) have both "clean" and "dirty" codes.

Table A.1: CPC and IPC Codes for Clean Electricity Generation Technologies

Sub-sector	Code	Description
Wind Energy	F03D	Wind motors
	H01L27/142	Devices consisting of a plurality of semiconductor components sensitive to infra-red radiation, light - specially adapted for the conversion of the energy of such radiation into electrical energy
	Y02E10/70	Wind energy
Solar Energy	E04D13/18	Aspects of roofing for energy collecting devices - e.g. incl. solar panels
	F03G6	Devices for producing mechanical power from solar energy
	F24J2	Use of solar heat e.g. solar heat collectors
	F26B3/28	Drying solid materials or objects by processes involving the application of heat by radiation e.g. from the sun
	H01L31/04	Semiconductor devices sensitive to infra-red radiation, light - adapted as conversion devices
	H02N6	Generators in which light radiation is directly converted into electrical energy
	Y02E10/40	Solar thermal energy, e.g. solar towers
	Y02E10/50	Photovoltaic [PV] energy
	Y02E10/60	Thermal-PV hybrids
Renewables	Y02B10	Integration of renewable energy sources in buildings
	Y02E10	Energy generation through renewable energy sources
Nuclear Energy	Y02E30	Energy generation of nuclear origin
Marine Energy	E02B9/08	Tide or wave power plants
	F03B13/10	Submerged units incorporating electric generators or motors characterized by using wave or tide energy
	F03B13/12	Submerged units incorporating electric generators or motors characterized by using wave or tide energy
	F03G7/05	Ocean thermal energy conversion
	Y02E10/30	Energy from the sea, e.g. using wave energy or salinity gradient
Hydro Energy	Y02E10/20	Hydro energy
Geothermal Energy	F03G4	Devices for producing mechanical power from geothermal energy
	F03G7/04	Mechanical-power-producing mechanisms - using pressure differences or thermal differences occurring in nature
	F24J3	Production or use of heat, not derived from combustion - using natural or geothermal heat
	Y02E10/10	Geothermal energy
Enabling Technologies	Y02B70/30	Systems integrating technologies related to power network operation and ICT for improving the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as CCMT in the buildings sector or as enabling technology in buildings sector.
	Y02B90/20	Systems integrating technologies related to power network operation and communication or information technologies mediating in the improvement of the carbon footprint of the management of residential or tertiary loads, i.e. smart grids as enabling technology in buildings sector
	Y02E40/70	Smart grids as climate change mitigation technology in the energy generation sector
	Y02E60	Enabling technologies (storage, hydrogen. . .)
	Y02E60/10	Energy storage using batteries, capacitors, Mechanical energy storage, e.g. flywheels or pressurised fluids
	Y02E60/30	Hydrogen Technology
	Y02E60/50	Fuel Cells
	Y02E60/70	Systems integrating technologies related to power network operation and communication or information technologies mediating in the improvement of the carbon footprint of electrical power generation, transmission or distribution, i.e. smart grids as enabling technology in the energy generation sector
	Y04S	Systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids.

Table A.2: CPC and IPC Codes for Grey Electricity Generation Technologies

Sub-sector	Code	Description
Energy Efficiency	B01J8/20	Chemical or physical processes (and apparatus therefor) conducted in the presence of fluidised particles, with liquid as a fluidising medium
	B01J8/24	Chemical or physical processes (and apparatus therefor) conducted in the presence of fluidised particles, according to fluidised bed furnaces
	C10J3	Production of combustible gases containing carbon monoxide from solid carbonaceous fuels
	F01K17/06	Use of steam or condensate extracted or exhausted from steam engine plant; Returning energy of steam, in exchanged form, to process, e.g. use of exhaust steam for drying solid fuel of plant
	F01K23	Plants characterised by more than one engine delivering power external to the plant, the engines being driven by different fluids
	F01K27	Plants for converting heat or fluid energy into mechanical energy; use of waste heat;
	F01K3	Plants characterised by the use of steam or heat accumulators, or intermediate steam heaters, therein
	F01K5	Plants characterised by use of means for storing steam in an alkali to increase steam pressure, e.g. of Honigmann or Koenemann type
	F02B1/12	Engines characterised by fuel-air mixture compression ignition
	F02B11	Engines characterised by both fuel-air mixture compression and air compression, or characterised by both positive ignition and compression ignition, e.g. in different cylinders
	F02B13/02	Engines characterised by the introduction of liquid fuel into cylinders by use of auxiliary fluid; Compression ignition engines using air or gas for blowing fuel into compressed air in cylinder
	F02B3/06	Engines characterised by air compression and subsequent fuel addition; with compression ignition
	F02B49	Methods of operating air - compressing compression - ignition engines involving introduction of small
	F02B7	Engines characterised by the fuel-air charge being ignited by compression ignition of an additional fuel
	F02C3/20	Gas turbine plants characterised by the use of combustion products as the working fuel
	F02C3/32	Gas turbine plants characterised by the use of combustion products as the working fuel
	F02C3/34	Gas turbine plants characterised by the use of combustion products as the working fuel
	F02C3/36	Gas turbine plants characterised by the use of combustion products as the working fuel
	F02C6/10	Combinations of gas-turbine plants with other apparatus; Supplying working fluid to a user, e.g. a chemical process, which returns working fluid to a turbine of the plant
	F02C7/30	Gas turbine plants - Preventing corrosion in gas-swept spaces
	F02G5	Profiting from waste heat of combustion engines;
	F22B31	Modifications of boiler construction, or of tube systems, dependent on installation of combustion apparatus; Arrangements or dispositions of combustion apparatus
	F22B33/14	Steam generation plants, e.g. comprising steam boilers of different types in mutual association; Combinations of low- and high-pressure boilers
	F22G	Superheating of steam (steam separating arrangements in boilers)
	F23B10	Combustion apparatus characterized by the combination of two or more combustion chambers (using only solid fuel)
	F23B30	Combustion apparatus with driven means for agitating the burning fuel; Combustion apparatus with driven means for advancing the burning fuel through the combustion chamber
	F23B70	Combustion apparatus characterized by means for returning solid combustion residues to the combustion chamber
	F23B80	Combustion apparatus characterized by means creating a distinct flow path for flue gases or for non-combusted gases given off by the fuel
	F23C1	Combustion apparatus specially adapted for combustion of two or more kinds of fuel simultaneously or alternately, at least one kind of fuel being fluent
	F23C10	Apparatus in which combustion takes place in a fluidised bed of fuel or other particles
	F23C5/24	Combustion apparatus characterized by the arrangement or mounting of burners; Disposition of burners to obtain a loop flame.
	F23C6	Combustion apparatus characterized by the combination of two or more combustion chambers (using fluent fuel)
	F23D1	Burners for combustion of pulverulent fuel
	F23D17	Burners for combustion simultaneously or alternatively of gaseous or liquid or pulverulent fuel
	F23D7	Burners in which drops of liquid fuel impinge on a surface
	F27B15	Fluidised-bed furnaces; Other furnaces using or treating finely-divided materials in dispersion
	Y02E20/10	Combined combustion
	Y02E20/30	Technologies for a more efficient combustion or heat usage
	Y02E40	Technologies For An Efficient Electrical Power Generation, Transmission Or Distribution
Biomass and Waste	C10L5/40	Solid fuels essentially based on materials of non-mineral origin - animal or vegetable substances; sewage, town, or house refuse; industrial residues or waste materials
	F01K25/14	Plants or engines characterized by use of industrial or other waste gases
	F02B43/08	Engines or plants operating on gaseous fuel generated from solid fuel, e.g. wood
	Y02E20	Combustion Technologies With Mitigation Potential (E.G. Using Fossil Fuels, Biomass, Waste, Etc.)
	Y02E50	Technologies for the production of fuel of non-fossil origin (Biofuels, e.g. bio-diesel, Fuel from waste, e.g. synthetic alcohol or diesel)

Table A.3: CPC and IPC Codes for Dirty Electricity Generation Technologies

Sub-sector	Code	Description
Traditional Fossil Fuels	C10J	Production of fuel gases by carburetting air or other gases
	C10L1	Liquid carbonaceous fuels; Gaseous fuels; Solid fuels
	C10L3	Gaseous fuels; Natural gas; Synthetic natural gas obtained by processes not covered by subclass C10G, C10K; Liquefied petroleum gas
	C10L5	Solid fuels
	F01K	Steam engine plans; steam accumulators; engine plants not otherwise provided for engines using special working fluids or cycles
	F02C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
	F22	Steam generation
	F23	Combustion apparatus; combustion processes
	F24J	Production or use of heat not otherwise provided for
	F27	Furnaces; kilns; ovens; retorts
	F28	Heat exchange in general

A.4 Inventor-Level Patenting Outcomes

To determine how often an inventor patents, we look at the number of patent families of different types (e.g., clean) that are connected to inventor i in year t. We use the first application in that family where the inventor's name is mentioned to assign a year for the family for that inventor.

Imagine an inventor applied for a patent that is classified both as "renewable energy" and as "grey" (this is a rare but possible case concerning only 3.6% of renewable energy families). Using our basic definition of "clean", this inventor would be noted as having one "clean" patent and one "grey" patent. However, using the broader definition of "clean", the inventor would only have one "grey" patent and zero "clean" ones.

Note that, with our baseline definition, the patent is therefore counted twice, once as "clean" and once as "grey." While this has no bearing on our regression analyses, which center on clean patenting, it does mean that in Section 2, the inventor is labeled as "Clean and Grey/Dirty." If we adopt the broader definition of "clean", the entire patent family is then classified as "grey", and consequently, so is the inventor.

We construct an alternative count of inventor-level clean families by weighting families by the number of citations they received. The number of citations received is often used as a proxy of patent quality (Jaffe et al. 2000; Jaffe and Rassenfosse 2017). Our weighting procedure lets us give more weight to families that may be of higher quality. Specifically, for a family filed in year t, the weight is equal to the ratio of the number of citations the family received within three years over the number of citations that the average energy family filed in year t received.

This weighting approach presents two defining features: 1) it uses a particular time window (three years in our baseline measure) and 2) it makes the weight relative to the citation count of the average energy family filed in that *same year* (as opposed to the average energy family filed in any year). We provide further explanations regarding these features below.

First, we use a particular time window because the older a patent family is, the more chances there are for others to cite it. Comparing old and new patents directly on their number of citations wouldn't be inappropriate since newer ones haven't had as much time to get cited. For this reason, we count citations that occur within a particular time window. We use three years in our baseline measure but, as an extra check, we also look at citations from the first five years.

In fact, since we're using citations from a fixed time frame to compare patents, the exact time frame shouldn't change much as long as citations happen at about the same rate over time for all patents. In our sample, citations peak on average after four years, and so our robustness check using citations received within five years ensure that our measure covers the majority of citations.

Second, we use the citation count of the average energy family filed in the same year in the denominator which makes the weight relative to the citation behavior of a contemporaneous family. This is useful because citation patterns may change significantly over time without necessarily indicating a change in quality. For example, the average family filed in 2000 may have a lower number of citations received within three years compared to a family filed in 2014, simply because the overall inventors and firms in the economy, and thereby a citing pool of patents, was much larger in 2014. But this does not necessarily mean the 2000 families are of lower value.

Another issue may arise since the 2022 version of PATSTAT provides good coverage of applications only up to 2019, and the number of citations that occurred within 3 or 5 years for a family filed in, e.g., 2017, may be incomplete. Constructing citation weights based on the average behavior of the energy families filed in the same year circumvents these potential problems.

We also construct an alternative count of inventor-level clean families by weighting families by the number of coinventors that are listed on the patent. In this case, the weight equals $1/n$ where n is the total number of coinventors on the patent. So if two inventors worked on a "clean" patent together, each would get credit for half a patent. We use this approach to avoid double-counting and to facilitate comparisons to extensive margin responses in Section 5.

Finally, while we can easily observe when inventors produce their first patent, it is more difficult to ascertain when they exit. For this reason, if an inventor didn't patent in a year but did later on, we impute that they produced zero patents that year. But after the last year we observe a patent from an inventor, we do not impute any more data. That means the record for each inventor stops the last year in which they produced a patent family.

A.5 Natural Gas Price Data

We use data on natural gas prices from the International Energy Agency (2020). Prices are available for three sectors: electricity generation, industry, and households. Our baseline prices use industrial prices because the coverage of prices for electricity is much poorer, and the industrial prices are highly correlated with electricity sector prices. The International Energy Agency (2020) natural gas prices are in nominal U.S. dollars per megawatt-hour. As discussed in the text, all econometric analysis in the paper includes time fixed effects, which absorb common time-varying factors including changes in the value of U.S. dollars due to inflation, so the results are invariant to using prices in real terms.

A.6 Ancillary Data for Regressions

We use country-year level data from the International Energy Agency (2019) on government spending on energy RD&D, both in aggregate and specifically for low-carbon technologies. Country-year level data on GDP and GDP per capita in 2017 U.S. dollars purchasing power parity terms come from the World Bank (2020a, 2020b).

A.7 Construction of Exposure Measures

As explained in the main manuscript, our baseline inventor-specific prices take the following form:

$$\ln P_{it} = \sum_j s_{ij} \sum_c \frac{s_{jc} GDP_c}{\sum_c s_{jc} GDP_c} \ln P_{ct},$$

where

- P_{ct} represents the average tax-inclusive natural gas price in country c during year t. Our baseline approach uses industry prices. However, for robustness checks, we introduce alternative measures based on prices in the electricity generation and household sectors. Furthermore, price data might be incomplete for some countries. In our primary approach, we construct prices only for countries with data consistently available from 2000 to 2017 or with at most one year missing. This approach yields what we term a "balanced" panel of prices. For further robustness, we also formulate an "unbalanced" version, incorporating all available country-year price data, irrespective of its duration or consistency.

- GDP_c represents the average GDP of country c from 1990 to 2018, expressed in PPP terms using constant 2017 international dollars. For added robustness, we also consider measures without GDP-weighting the prices.

- s_{jc} quantifies firm j's exposure to country c. In our primary approach, this is determined by the proportion of firm j's energy patents in country c spanning 1990 to 2015. To enhance robustness, we consider three alternative methods to compute this weight: 1) Based on the proportion of *all* of firm j's patents in country c from 1990 to 2015. 2) Using the proportion of firm j's *energy* patents in country c during a pre-defined period from 1990 to 2000. 3) Reflecting the proportion of *all* of firm j's patents in country c within the same pre-defined period from 1990 to 2000. Firms lacking patent activity during the pre-period are allocated uniform weights across all countries.

- s_{ij} measures the association between inventor i and firm j. Specifically, it's determined by the fraction of patent families of inventor i linked with firm j. This weight is constructed using the full time series of each inventor's activities. Inventors who file independently, often termed "garage" inventors, are presumed to be influenced by the price in their country of residence.

B Inventor Disambiguation

B.1 Background

The challenge of accurately distinguishing authors and institutions is a significant concern in patent data. The same entity, be it an organization or an individual, can be represented with variations in their names, depending on the channels they've used for patent applications over time. Such inconsistencies arise from spelling errors, typographical mistakes, and different name variants, among others. While the initial PATSTAT data provided names and addresses of inventors, it lacked a system to uniquely identify inventors chronologically. For our study, creating a consistent and unique identifier for each inventor is crucial as we aim to monitor patents registered by individual inventors over time. Patent data frequently suffers from name misspellings, leading to multiple variants for a single inventor's name (e.g., JONSSON, NILS-AKE might also appear as JONSSON, NILS A.). The primary difficulty in disambiguation lies in associating all variants of an inventor's name without inadvertently merging distinct inventors with similar names.

Numerous studies have endeavored to disambiguate names and establish trustworthy inventor identifiers within patent databases, predominantly within the USPTO and EPO repositories. For instance, Li et al. (2014) (hereforth LLDD) undertook a disambiguation exercise on patents registered with the USPTO between 1975 and 2010, yielding unique identifiers for each inventor within their sample timeframe. A parallel initiative on European patent data was carried out by Coffano and Tarasconi (2014), crafting distinct inventor identifiers for the EPO database spanning 1970 to 2010. Research endeavors focusing on tracking activities at the inventor level typically lean on such disambiguated databases.

For our current study, given the absence of previous disambiguation work on the most recent PATSTAT dataset, our aim is to design straightforward disambiguation rules for the PATSTAT database. This will facilitate the efficient identification of unique inventors over time, while significantly alleviating issues related to name misspelling.

B.2 Harmonized Names in PATSTAT Data

PATSTAT provides multiple name versions for a single inventor: the nonharmonized inventor name (person name), the name in its original language, and several harmonized renditions.

The initial harmonized version in PATSTAT is the DOCDB standardized name, designated for applicant and inventor names set for inclusion in DOCDB. An issue with the DOCDB standardized name is its occasional misalignment with accurate person names. For instance, an inventor named "Charquet, Daniel" might be erroneously linked with "MARDON JEAN-PAUL", a clear mismatch. Such errors are particularly prevalent in USPTO patents.

Another available harmonized version is the HAN name, formulated primarily by the OECD HAN (Harmonized Applicant Name) project of the OECD. However, this applies solely to patent applicants and excludes inventors. ' The final harmonized version is the PATSTAT standardized name (PSN name), derived through automation and manual refinements, with non-harmonized names being directly lifted from the person name variable[1]. This standardization aims to rectify spelling variations, typographical errors, and acronym inconsistencies.

1. Details on PSN name and PSN ID construction in PATSTAT can be found in Magerman et al. (2006)

While PSN name harmonization undoubtedly reduces data discrepancies, it can fall short. A number of issues arise in particular related to presence of special characters (e.g., “TAKAHASHI, YUKIO” and “TAKAHASHI YUKIO”) or the treatment of middle names (e.g., “JONSSON NILS AKE” vs. “JONSSON NILS A.” or “SCHULZ, JOHANN G.” vs. “SCHULZ, JOHANN G. D.”).

Such issues are widespread, necessitating further refinement to the harmonized name variables for more accurate inventor identification. In addition, existing IDs anchored solely to harmonized name spellings disregard the locational/address data, potentially misidentifying distinct inventors with identical names.

B.3 Simple Rules for Further Name Disambiguation

As outlined in the previous section, two primary challenges arise when directly utilizing the PATSTAT standardized name ID (PSN ID) as a singular inventor identifier: 1) Variations in the spelling or format of an inventor’s name lead to multiple identifiers for the same individual. 2) Conversely, distinct inventors sharing identical names may be erroneously grouped under one identifier.

For our analysis, we devised three straightforward rules to clean PATSTAT standardized names (PSN name) and forge unique inventor identifiers based on these refined names. We then examine the efficacy of these rules by comparing our approach to the disambiguated USPTO inventor data from LLDD.

We implemented the series of different rules:

- Rule 0: No modification (i.e., keeping the PSN name as provided by PATSTAT)
- Rule 1: Character cleaning and punctuation cleaning
- Rule 2: Rule 1 + changing all the middle names to middle initials
- Rule 3: Rule 1 + Rule 2 + keeping only 1 middle initial for people with multiple middle names

We also created two new inventor identifiers:

- Inventor ID 1: unique disambiguated PSN names as inventor identifier (without using any address information)
- Inventor ID 2: unique combinations of disambiguated PSN names and reported country of residence as inventor identifier

B.4 Comparing to Li et al. (2014)

To assess the efficacy of our disambiguation rules and the resultant inventor IDs for PSN names in PATSTAT, we compare our approach to the disambiguated inventor IDs of LLDD. To do so, we first narrow our PATSTAT sample to inventors that filed granted energy-related patents through the USPTO between 1975 and 2010. This data subset is then integrated with the OECD triadic patent family database via PATSTAT IDs, allowing us to retrieve the original USPTO IDs for these patents. Using these USPTO IDs, we extract an identical subset of patent grants from LLDD.

Table B.1 displays our data summary. We found more unique inventors using the original PSN names (38,853) than in LLDD (36,546). This suggests that the PSN IDs might be mixing up some inventors, seeing them as different people when they're actually the same. Consequently, we also find a higher average patent applications per inventor in LLDD.

Table B.1: Summary Statistics of Comparable Sample Used for Analysis

	PATSTAT subsample	Li et al. (2014) subsample
Number of Unique Inventors	38,853	36,546
Number of Patent Grants	26,018	26,018
Number of OECD Triadic Families	20,257	20,257
Number of DOCDB Families	22,135	-
Number of Inventors w/ Reported Address in 2 Countries	199	252
Number of Inventors w/ Reported Address in 3 Countries	3	6
Average Number of Patent Applications Per Inventor	0.670	0.712

Note: The number of unique inventors from PATSTAT sample is identified by the number of unique PSN IDs (hence unique PSN names).

Next, we match the inventor IDs from LLDD with our various cleaned-up versions of PATSTAT inventor IDs. We start by pairing inventors in each patent record using their cleaned-up last names. If a patent record has more than one inventor with the same last name, we use both their first and last names to match them. This ensures that each name from PATSTAT is checked against all its versions in the LLDD data.

Table B.2 gives an overview of how well each method works.[2] Row 1 displays the total number of unique inventors in LLDD. Row 2 the total number of unique inventors in PATSTAT with the original PSN ID. These totals stay the same, no matter which rules we use. They're there to help compare results. Row 3 reports the number of unique inventors in PATSTAT based on the rule used in each column.

Rows 4 and 5 provide information on mismatches between the two sets of data. Row 4 shows instances where an inventor has a unique ID in LLDD but gets multiple IDs in PATSTAT. For example, using Rule 1 with inventor ID 1, 1,298 inventors from LLDD get treated as different people in PATSTAT when they should be the same. Row 5 is the opposite: it lists cases where PATSTAT thinks inventors are the same person, but LLDD treats them as different people. There are 760 such instances.

Rows 6 and 7 tell us the number of inventors we are not able to match between the two datasets. These are less informative because as long as these inventors show up only one time in the data, this will not lead to over or under disambiguation. As a result, the numbers in Row 6 and 7 are simply an indication of the matched sample size.

Finally, Row 8 shows the number of correctly matched inventors. This is calculated by taking the unique inventors in PATSTAT and subtracting the ones with matching problems (multiple match in either way and unable to match). The percentage of these correctly matched inventors (Row 9) is then the correctly matched number divided by PATSTAT's total unique inventors based on the particular rule used in each column.

2. We do not include results for Rule 0 (which doesn't change the PSN names) because very few matches were found using this rule.

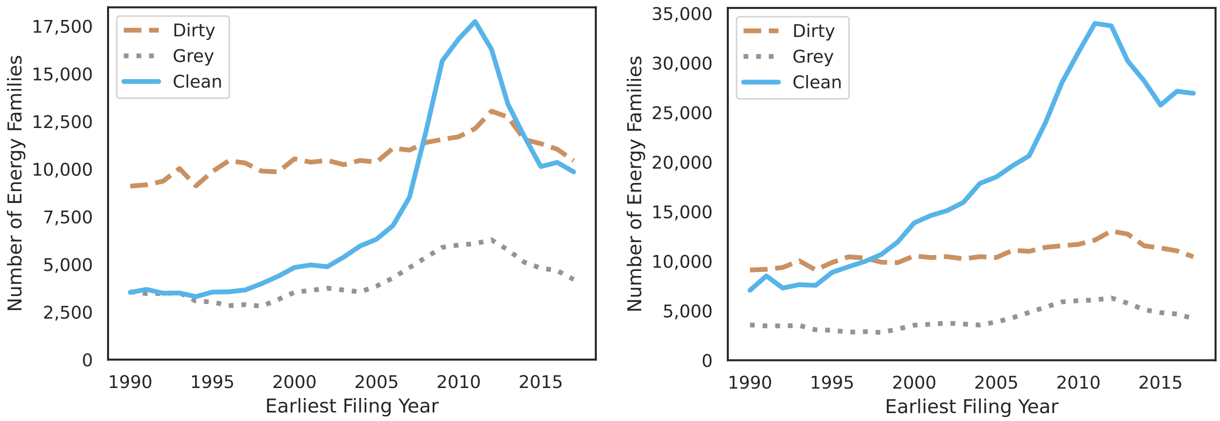
The fraction of correctly matched inventors is largest for Column 5 with 92.1%. This corresponds to using Rule 3 with inventor ID 1.

Table B.2: Summary of Performance of Different Disambiguation Rules

	Rule 1& INV ID 1	Rule 1& INV ID 2	Rule 2& INV ID 1	Rule 2& INV ID 2	Rule 3& INV ID 1	Rule 3& INV ID 2
Number of unique inventors in LLDD	**36,546**	**36,546**	**36,546**	**36,546**	**36,546**	**36,546**
Number of unique inventors in PATSTAT (by PSN ID)	38,853	38,853	38,853	38,853	38,853	38,853
Number of unique inventors in PATSTAT	37,170	37,440	36,147	36,472	36,257	36,565
Inventors with non-unique IDs in PATSTAT but unique ID in LLDD	1,298	1,395	522	628	572	668
Inventors with non-unique IDs in LLDD but unique ID in PATSTAT	760	619	894	726	754	699
Number of inventors in LLDD we cannot match to PATSTAT	1,417	1,417	1,416	1,417	1,417	1,417
Number of inventors in PATSTAT we cannot match to LLDD	1,591	1,601	1,530	1,546	1,550	1,570
Number of correctly matched inventors	33,521	33,825	33,201	33,572	33,381	33,628
Fraction of correctly matched inventors	0.902	0.903	0.918	0.920	0.921	0.920

C Descriptives

C.1 Trends in Families Over Time



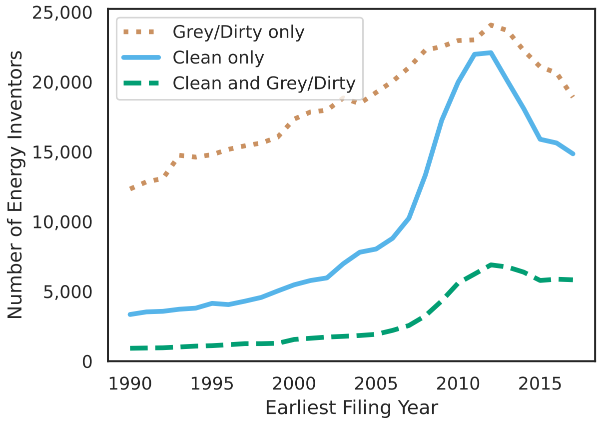
(a) Baseline Definition of Clean

(b) Broader Definition of Clean

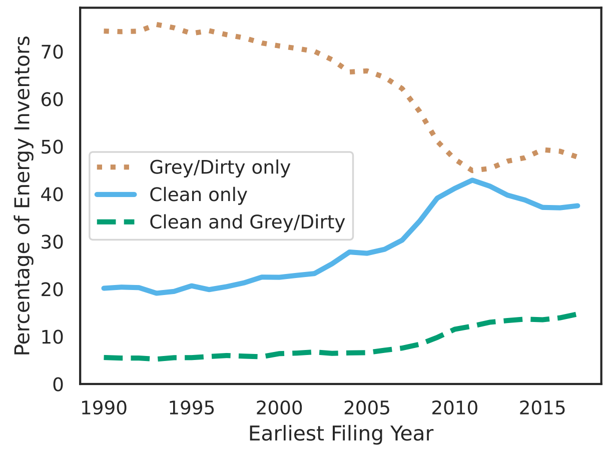
Figure C.1: Patent Families by Type Over Time

Note: The figures plot the number of patent families classified as clean, grey, and dirty over time. Panel a uses the baseline definition of clean and Panel b uses the broader definition.

C.2 Inventor Types

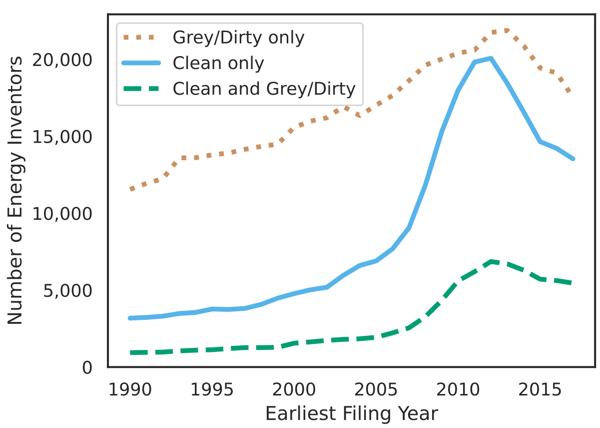


Levels

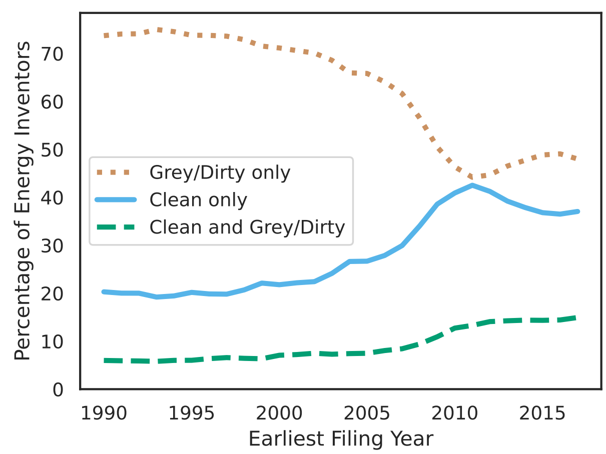


Percentage

(a) Energy Inventors with Energy Patents in at least Two Different Years



Levels



Percentage

(b) Energy Inventors with at least Two Energy Patents

Figure C.2: Trends in the Number and Composition of Energy Iventors over Time

Note: These figures are alternative versions of Figures 1a and 1b from the main text. The figures illustrate the extent to which energy inventors specialize in either clean, grey, or dirty patenting. We focus on inventors' global patent portfolios for inventors with at least one energy patent in an OECD country after 1990. To construct the graphs, we first identify inventors with at least one energy family filed in year t, and then classify them according to their last three years of patenting activity.

Table C.1: Energy Inventors by Type

(a) Using the Baseline Definition of Clean

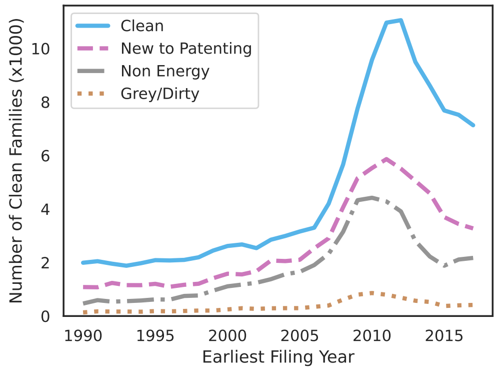
Inventor Type	All Inventors	Serial Inventors	Serial Inventors (2 years +)	Energy Serial Inventors	Top 10th Inventors
Grey/Dirty only	60%	55%	52%	50%	24%
Clean only	29%	29%	29%	28%	23%
Clean and Grey/Dirty	11%	16%	18%	22%	53%
Total Number of Energy Inventors	726,049	459,972	393,815	287,734	76,396

(b) Using the Broader Definition of Clean

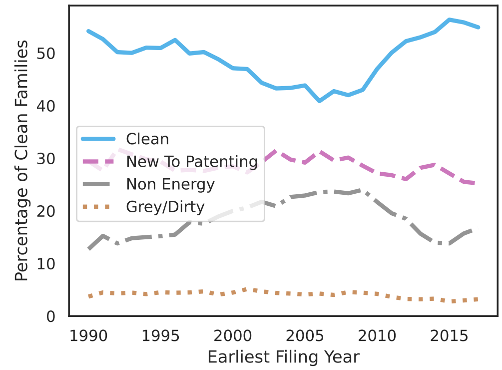
Inventor Type	All Inventors	Serial Inventors	Serial Inventors (2 years +)	Energy Serial Inventors	Top 10th Inventors
Grey/Dirty only	45%	41%	39%	37%	18%
Clean only	44%	43%	42%	39%	29%
Clean and Grey/Dirty	11%	16%	19%	24%	53%
Total Number of Energy Inventors	982,805	636,405	545,708	401,262	104,687

Note: These tables show the average share of energy inventors by type for different definitions of clean. These shares correspond to the average of the trends shown on Figures 1a, 1b and C.2. Details about the different definitions of clean are provided in Subsection A.3.

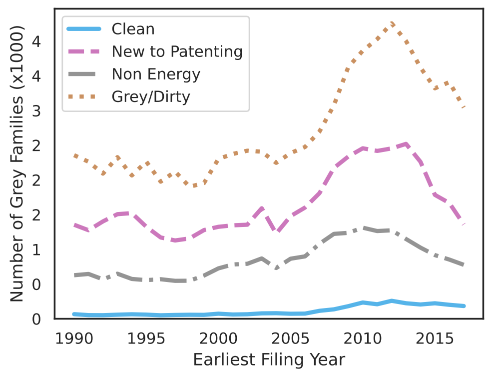
C.3 Clean, Grey, and Dirty Patent Families by Origin of Inventors



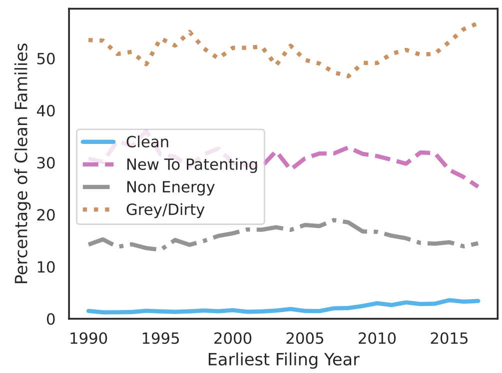
(a) Clean - Levels



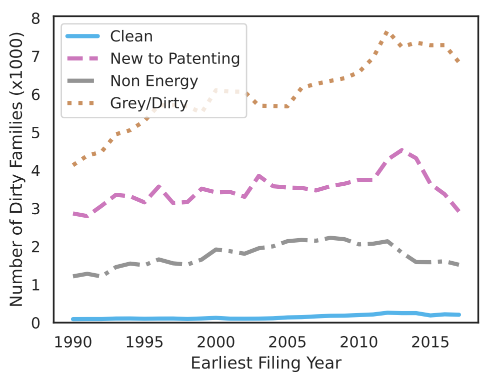
(b) Clean - Percentage



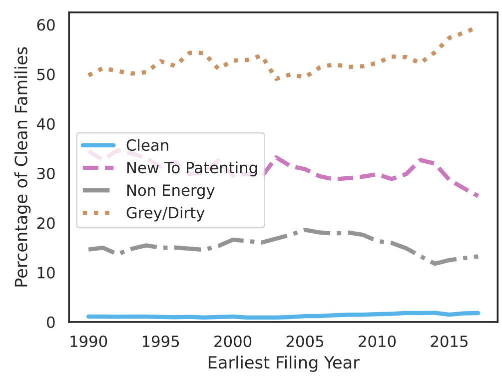
(c) Grey - Levels



(d) Grey - Percentage



(e) Dirty - Levels

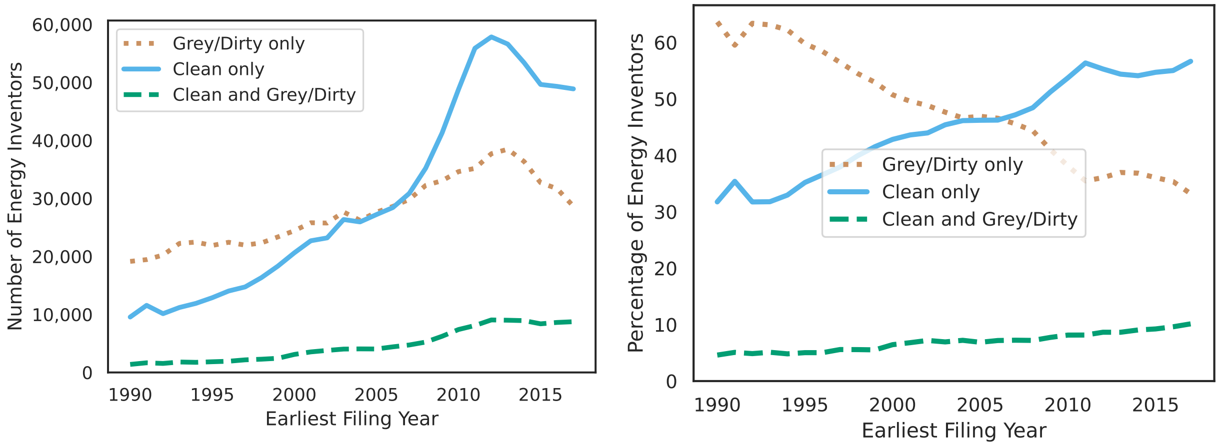


(f) Dirty - Percentage

Figure C.3: Clean, Grey, and Dirty Patent Families by Origin of Inventor

Note: These figures illustrate the types of inventors that produce clean, grey, and dirty patent families over time. They plot the trend over time in the number and share of families connected to incumbents, inventors new to patenting, inventors with previous patents outside the set of energy technologies under study, and inventors with previous energy technology patents. Families with multiple inventors are fractionally attributed to the inventors to avoid double-counting. Figures C.3a and C.3b are reproductions of Figures 1c and 1d from the main text for convenience.

C.4 Descriptives using a Broader Definition of Clean

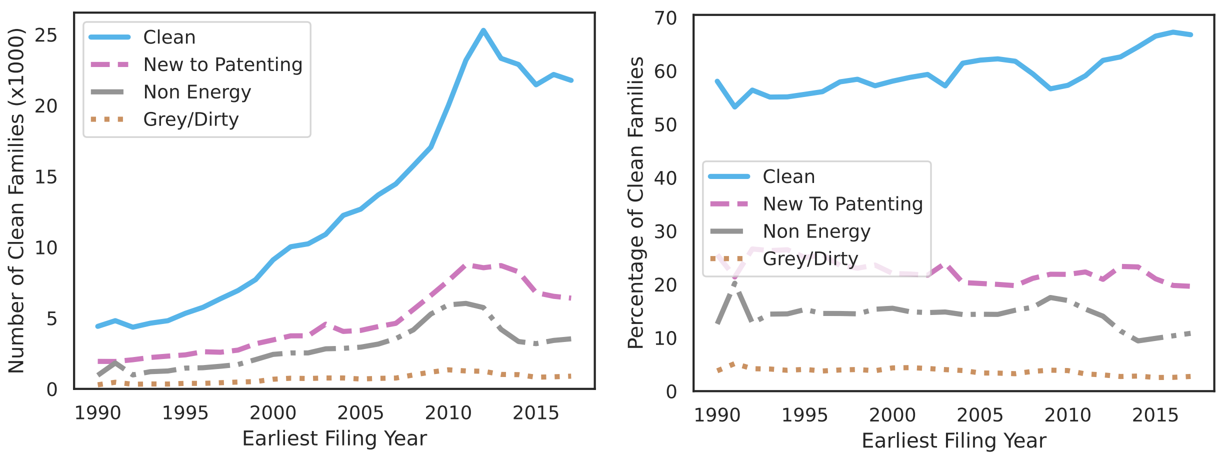


(a) Levels

(b) Percentage

Figure C.4: Energy Inventors By Type (All Inventors)

Note: These figures are alternative versions of Figures 1a and 1b from the main text using a broader definition of clean as described in Subsection A.3.



(a) Clean Broader - Levels

(b) Clean Broader - Percentage

Figure C.5: Clean Patent Families by Origin of Inventor

Note: These figures are alternative versions of Figures 1c and 1d from the main text using a broader definition of clean as described in Subsection A.3.

C.5 Other Information about Patent Codes

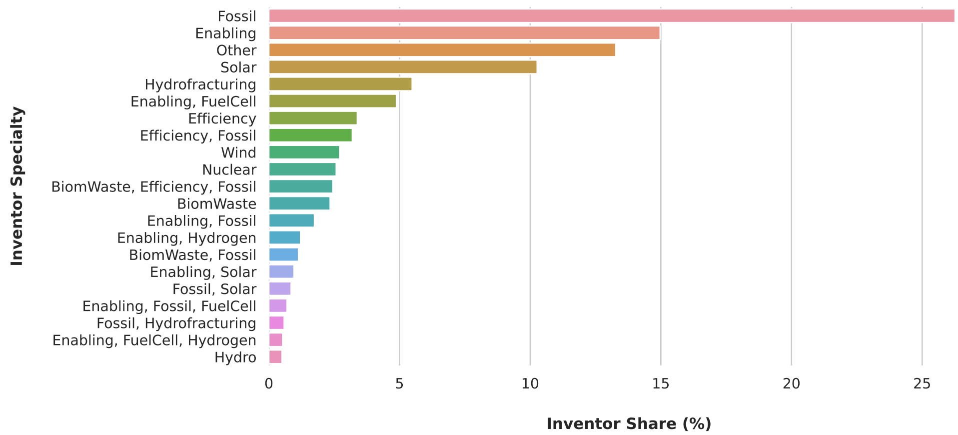


Figure C.6: Technological Areas Most Often Combined by Energy Inventors

Note: This bar plot depicts the specific technology areas that energy inventors focus on. The highest bar shows that over 25% of the energy inventors in our sample have patents exclusively in fossil-related technologies, while just over 15% specialize in enabling technologies. The most frequent other clean area is solar with about 10%. The label “Other” corresponds to all other combinations of technologies that are not listed.

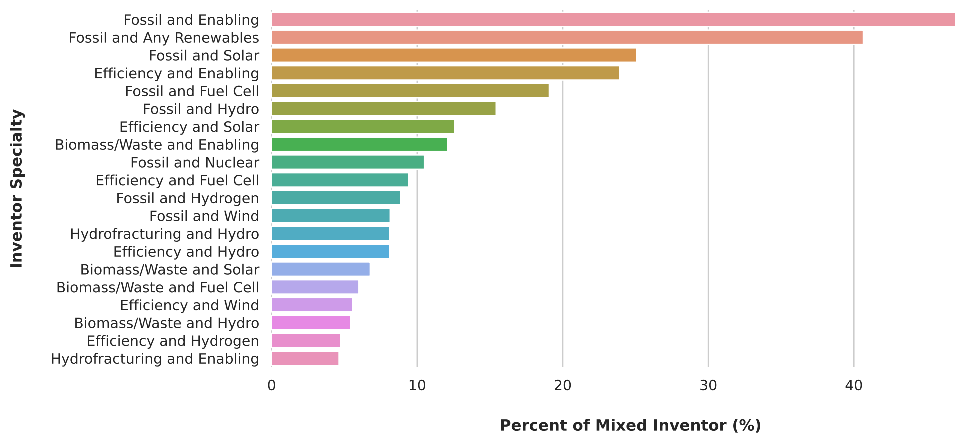


Figure C.7: Clean and Grey/Dirty Technological Areas Most Often Combined by Inventors

Note: This graph shows the 20 most common combinations of clean and grey/dirty areas. The highest bar indicates that about 45% of mixed-type inventors combine technologies related to fossil and enabling. 40% also combine fossil and any renewables. The percentages are calculated such that an inventor that combines fossil, enabling, and renewable technologies will count towards both the first and the second bars, as well as one or more other bars for the specific renewable technologies they combine.

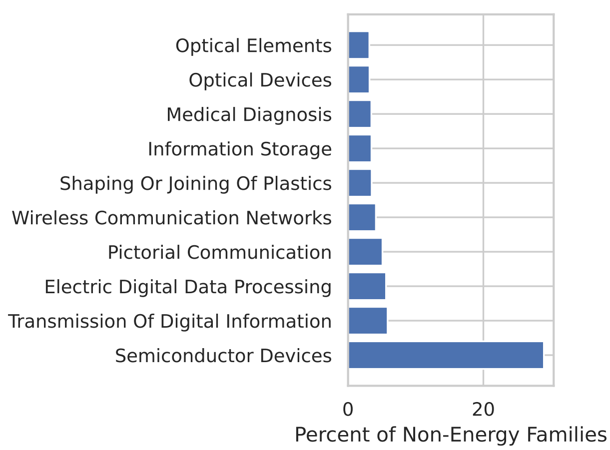


Figure C.8: CPC Codes of Non-Energy Patents of Clean Entrants

D Summary Statistics

D.1 Inventor-Level Summary Statistics

Table D.1: Summary Statistics for Patenting Variables - Baseline Definition of Clean

	count	mean	sd	min	p50	p90	p95	p99	max
Simple Count	1086250	0.50	1.10	0.00	0.00	1.00	2.00	5.00	113.00
Coinventor-Weighted	1086250	0.21	0.53	0.00	0.00	0.60	1.00	2.00	76.50
Citation-Weighted (3 years)	1086250	0.53	1.66	0.00	0.00	1.40	2.51	6.68	173.41
Citation-Weighted (5 years)	1086250	0.53	1.76	0.00	0.00	1.39	2.54	7.03	171.64
Triadic	1086250	0.09	0.39	0.00	0.00	0.00	1.00	2.00	30.00
Triadic (Coinventor-Weighted)	1086250	0.03	0.18	0.00	0.00	0.00	0.20	0.83	31.50
Granted	1086250	0.36	0.85	0.00	0.00	1.00	2.00	3.00	46.00
Granted (Coinventor-Weighted)	1086250	0.14	0.39	0.00	0.00	0.50	1.00	1.83	49.00
Triadic Granted	1086250	0.08	0.37	0.00	0.00	0.00	1.00	1.00	30.00
Triadic Granted (Coinventor-Weighted)	1086250	0.03	0.17	0.00	0.00	0.00	0.20	0.67	31.50
More than 2 countries	1086250	0.24	0.64	0.00	0.00	1.00	1.00	3.00	37.00
More than 2 countries (Coinventor-Weighted)	1086250	0.09	0.30	0.00	0.00	0.33	0.50	1.11	38.00
More than 2 OECD	1086250	0.20	0.58	0.00	0.00	1.00	1.00	2.00	36.00
More than 2 OECD (Coinventor-Weighted)	1086250	0.08	0.27	0.00	0.00	0.25	0.50	1.00	37.00

Note: These summary statistics are for the sample of clean incumbent inventors used in the incumbent regressions.

Table D.2: Summary Statistics for Patenting Variables - Broader Definition of Clean

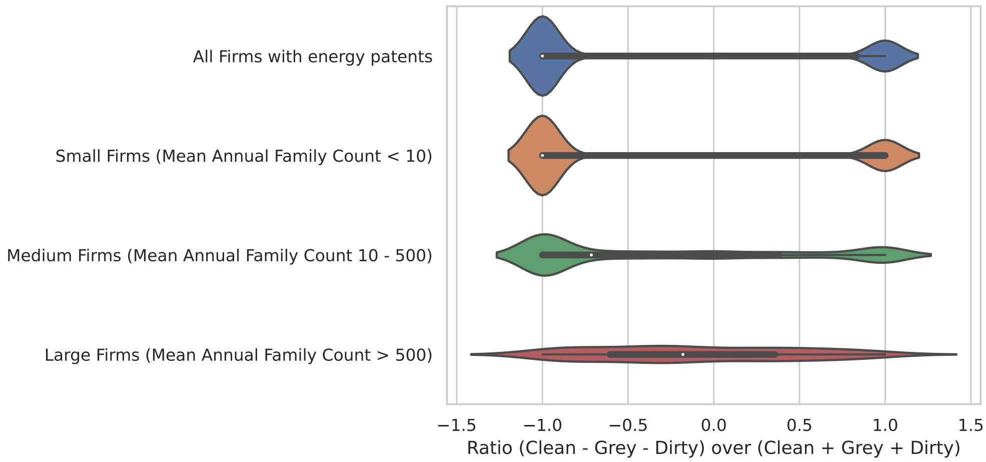
	count	mean	sd	min	p50	p90	p95	p99	max
Simple Count	2055150	0.67	1.57	0.00	0.00	2.00	3.00	7.00	98.00
Coinventor-Weighted	2055150	0.24	0.61	0.00	0.00	0.75	1.00	2.52	50.50
Citation-Weighted (3 years)	2055150	0.67	2.42	0.00	0.00	1.76	3.05	8.05	385.90
Citation-Weighted (5 years)	2055150	0.67	2.50	0.00	0.00	1.76	3.11	8.34	356.07
Triadic	2055150	0.13	0.50	0.00	0.00	0.00	1.00	2.00	50.00
Triadic (Coinventor-Weighted)	2055150	0.04	0.18	0.00	0.00	0.00	0.25	1.00	28.50
Granted	2055150	0.47	1.17	0.00	0.00	1.00	2.00	5.00	75.00
Granted (Coinventor-Weighted)	2055150	0.16	0.43	0.00	0.00	0.50	1.00	1.98	37.00
Triadic Granted	2055150	0.11	0.47	0.00	0.00	0.00	1.00	2.00	39.00
Triadic Granted (Coinventor-Weighted)	2055150	0.04	0.17	0.00	0.00	0.00	0.25	0.83	28.50
More than 2 countries	2055150	0.31	0.84	0.00	0.00	1.00	1.00	4.00	52.00
More than 2 countries (Coinventor-Weighted)	2055150	0.10	0.32	0.00	0.00	0.33	0.50	1.25	36.33
More than 2 OECD	2055150	0.27	0.79	0.00	0.00	1.00	1.00	3.00	52.00
More than 2 OECD (Coinventor-Weighted)	2055150	0.09	0.30	0.00	0.00	0.33	0.50	1.17	36.33

Note: These summary statistics are for the sample of clean incumbent inventors used in the incumbent regressions, based on the broader definition of clean as described in Subsection A.3.

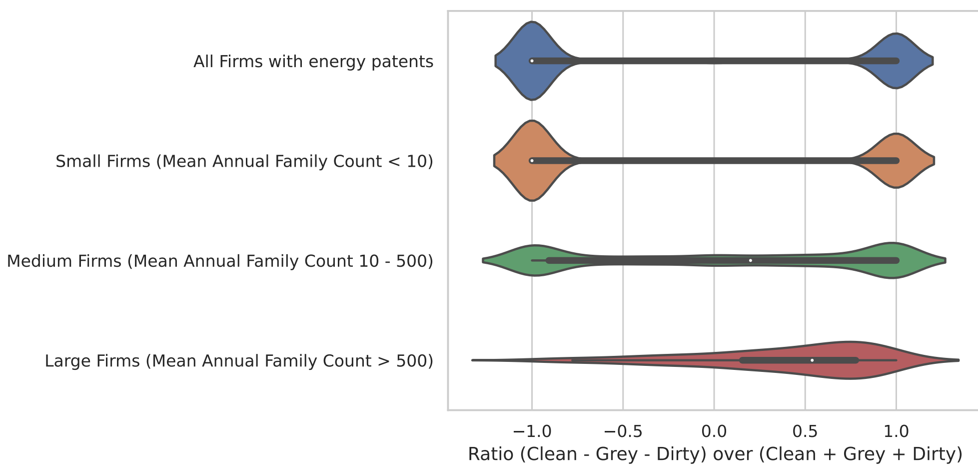
Table D.3: Summary Statistics for Different Measures of Natural Gas Prices - Incumbents Sample

	count	mean	sd	min	max
Prices GDP-Weighted Balanced (log, t-1)	1,065,105	32.6	12.2	5.51	73.5
Prices GDP-Weighted Unbalanced (log, t-1)	1,065,228	32.7	12.1	5.51	73.5
Prices Not GDP-Weighted Balanced (log, t-1)	1,065,105	37.5	12.5	5.51	73.5
Prices Not GDP-Weighted Unbalanced (log, t-1)	1,065,228	37.9	12.5	5.51	73.5

D.2 Firm-Level Summary Statistics



(a) Baseline Definition of Clean



(b) Broader Definition of Clean

Note: The graphs depict the distribution of firms based on their specialization degree. The x-axis consists of the following ratio: $\frac{FamilyCountClean - FamilyCountGrey - FamilyCountDirty}{FamilyCountClean + FamilyCountGrey + FamilyCountDirty}$, where $FamilyCountClean$ is the average number of clean patent families firm j filed annually between 1990 and 2014. This ratio holds a value of 0 when a firm files an equal number of clean and grey/dirty patent families. It registers a value of 1 when a firm exclusively specializes in clean patents and -1 when it focuses purely on grey or dirty patents. The graphs suggest that most firms in our sample are specialized in either clean or dirty. However, larger firms exhibit greater diversification, combining clean and grey/dirty patents. Notably, Figure D.1b emphasizes that when adopting the broader definition of clean, many larger firms focus predominantly on clean energy. This tendency can be attributed to sizeable conglomerates like Panasonic, which patent extensively on battery-related technologies and little on grey or dirty technologies.

Figure D.1: Density Plots for the Degree of Specialization

Table D.4: Firm-Level Summary Statistics

(a) Mean

		Family Count	Percent	Family Count	Percent in Energy				If Diversified	If Specialized in		
		Total	Energy	Energy	ReNu	Clean	Grey	Dirty		Clean	Grey/Dirty	
Row	Sample Description	1	2	3	4	5	6	7	8	9	10	Row
1	Firms with energy patents	11.2	45	1.2	25	43	16	41	0.1	0.4	0.5	1
2	Firms with Re/Nu patents	25.9	44	2.1	79	83	8	9	0.2	0.7	0.1	2
3	Firms with clean patents	19.7	41	1.7	49	87	5	8	0.2	0.8	0.0	3
4	Firms connected to energy inventors	11.2	45	1.2	25	43	16	41	0.1	0.4	0.5	4
5	Firms connected to Re/Nu inventors	17.8	36	1.5	38	56	14	31	0.2	0.5	0.4	5
6	Firms connected to clean inventors	15.8	37	1.4	33	58	13	30	0.2	0.5	0.3	6
7	Firms connected to non-energy entrants before the year of entry	52.2	10	2.8	28	54	13	34	0.3	0.4	0.3	7
8	New Firms connected to non-energy entrants the year of entry	52.7	31	3.4	59	73	10	17	0.3	0.5	0.1	8
9	All Firms connected to non-energy entrants the year of entry	43.6	27	2.8	59	73	9	18	0.3	0.6	0.1	9
10	Firms connected to grey/dirty inventors	18.6	38	1.5	11	22	23	54	0.2	0.1	0.7	10
11	Firms connected to grey/dirty entrants before the year of entry	46.3	18	2.7	21	42	17	41	0.3	0.3	0.4	11
12	New Firms connected to grey/dirty entrants the year of entry	88.9	24	5.3	45	63	12	25	0.4	0.4	0.2	12
13	All Firms connected to grey/dirty entrants the year of entry	71.2	23	4.2	41	58	14	28	0.4	0.4	0.2	13
14	Firms connected to new to patenting entrants the year of entry	61.0	12	3.3	40	63	11	27	0.4	0.4	0.2	14

(b) Median

		Family Count	Percent	Family Count	Percent in Energy				If Diversified	If Specialized in		
		Total	Energy	Energy	ReNu	Clean	Grey	Dirty		Clean	Grey/Dirty	
Row	Sample Description	1	2	3	4	5	6	7	8	9	10	Row
1	Firms with energy patents	2.0	33	0.7	0	0	0	0	0.0	0.0	1.0	1
2	Firms with Re/Nu patents	2.1	30	1.0	100	100	0	0	0.0	1.0	0.0	2
3	Firms with clean patents	2.2	25	0.7	44	100	0	0	0.0	1.0	0.0	3
4	Firms connected to energy inventors	2.0	33	0.7	0	0	0	0	0.0	0.0	1.0	4
5	Firms connected to Re/Nu inventors	2.6	19	0.5	0	75	0	0	0.0	0.0	0.0	5
6	Firms connected to clean inventors	2.4	20	0.5	0	86	0	0	0.0	0.0	0.0	6
7	Firms connected to non-energy entrants before the year of entry	8.3	4	0.3	1	60	0	13	0.0	0.0	0.0	7
8	New Firms connected to non-energy entrants the year of entry	4.3	13	0.8	67	98	0	0	0.0	1.0	0.0	8
9	All Firms connected to non-energy entrants the year of entry	4.2	11	0.6	67	100	0	0	0.0	1.0	0.0	9
10	Firms connected to grey/dirty inventors	2.1	21	0.5	0	0	0	64	0.0	0.0	1.0	10
11	Firms connected to grey/dirty entrants before the year of entry	6.4	7	0.5	0	33	0	29	0.0	0.0	0.0	11
12	New Firms connected to grey/dirty entrants the year of entry	10.2	8	1.0	33	77	0	7	0.0	0.0	0.0	12
13	All Firms connected to grey/dirty entrants the year of entry	8.9	8	0.8	27	67	0	10	0.0	0.0	0.0	13
14	Firms connected to new to patenting entrants the year of entry	8.9	5	0.4	25	77	0	6	0.0	0.0	0.0	14

Note: The tables present summary statistics of various firm samples. For instance, the first row examines firms that filed at least one energy patent between 1990 and 2014. In contrast, the 8th row delves into a specific subsample: firms that connected with a non-energy entrant in their year of clean entry but had no prior connection with them. Table D.4a reports values for the mean firm while Table D.4b reports values for the median firm.
Below is more information about each variable in the columns. All variables are calculated using firm-level patent data for the period between 1990 and 2014.

- "Family Count Total" (Column 1) is the average number of patent families filed annually, irrespective of type.
- "Percent Energy" is the proportion of energy-related patent families out of the total count.
- "Family Count Energy" is the average number of energy-related patent families, filed annually.
- The section labeled "Percent in Energy" breaks down firms' energy patent portfolio into the following categories: Renewables and Nuclear ("ReNu"), Clean (our broad definition of "Clean" that include enabling technologies), Grey, and Dirty.
- Columns "If Diversified" and "If Specialized in" show the mean or median values of binary variables that indicate whether a firm is diversified and if not, whether it i specialized in Clean or in Grey/Dirty. This classification relies on the following ratio:
  $\frac{FamilyCountClean - FamilyCountGrey - FamilyCountDirty}{FamilyCountClean + FamilyCountGrey + FamilyCountDirty}$.
  Where $FamilyCountType$ represents the average yearly count of patent families of type k filed by firm j between 1990 and 2014. The binary variables are constructed as follows:
  - Firms with a ratio greater than 0.8 are classified as specialized in Clean.
  - Firms with a ratio less than -0.8 are seen as specialized in Grey or Dirty.
  - Firms with a ratio between -0.8 and 0.8 are termed diversified.

Take-Aways from Table D.4

- Regarding firms that have at least one energy patent:

  From Row 1, we learn that, on average, these firms file 11.2 patents annually (Column 1), with 45% of these patents being energy-related (Column 2). In contrast, the median value for the total patent family count is significantly lower at 2.0 (Table D.4b Column 1). This suggests a skewed distribution with a long right tail, meaning that while the typical firm patents only two families per year, some firms patent extensively. Most firms specialize in clean or grey/dirty; about 10% only are diversified (Column 8).

- Regarding inventors that enter clean from non-energy:
  - Row 7: Before patenting in clean energy, non-energy entrants typically are connected with firms that: 1) patent more frequently than the average energy-patenting firm (51.8 in Column 1 vs 11.2 in Row 1 Column 1); 2) focus less on energy, with only 10% of their patents being related to energy (Column 2); 3) are more likely to be diversified (0.3 in Column 8 vs. 0.1 in Row 1).
  - Row 8: When non-energy inventors enter and file their first clean patent, we typically observe that they file patents with firms they have never patented with. The newly associated firms have a greater focus on energy (32% in Column 2 vs. 10% in Row 7) compared to the firms these inventors were previously patenting with (32% in Column 2 vs. 10% in Row 7). They are also considerably less likely to specialize in grey/dirty (0.1 in Column 10 vs. 0.3 in Row 7).

- Regarding inventors that enter clean from grey and/or dirty:
  - Row 11: Before patenting in clean, grey/dirty entrants are connected with firms that: 1) patent more frequently than the average grey/dirty firm (45.4 in Column 1 vs 18.6 in Row 10); 2) are not as heavily focused on energy, with their energy-related patents constituting only 19% of their portfolio (Column 2), compared to 38% for the average grey/dirty firm (Column 2 Row 10); 3) exhibit greater diversification between clean and grey/dirty technologies (reflected by a value of 0.3 in Column 8); 4) are less inclined to specialize solely in the grey/dirty sector (0.4 in Column 10 vs 0.7 in Row 10).
  - Row 12: When grey/dirty inventors enter clean, we observe that they tend to file patents with firms they have never patented with before. These newly associated firms patent significantly more than the firms these inventors were previously patenting with (85.2 in Column 1 vs 45.4 in Row 11). Additionally, these firms are more likely to be diversified (0.4 in Column 8 vs. 0.3 in Row 11) and less likely to specialize in grey/dirty technologies (0.2 in Column 10 vs. 0.4 in Row 11).

E Instrumental Variable Estimation

As described in Section 3, some estimates come from an instrumental variable strategy that utilizes variation in natural gas prices caused by the shale gas revolution. Since the model in equation 1 is nonlinear and contains inventor fixed effects, we use a control function approach to implement the instrumental variable strategy. Our approach is based on the control function method outlined in Lin and Wooldridge (2019). We start by estimating a first-stage linear regression of prices on the shale revolution instrument, as well as all other covariates used in estimating equation 1:

$$\ln P_{it-1} = \tilde{\beta}_z z_{it-1} + \tilde{\beta}_X X_{it-1} + \tilde{\gamma}_{t-1} + \tilde{\eta}_i + \tilde{u}_{it-1}, \tag{E.1}$$

where z_{it} is an inventor-specific measure of the binary instrument for the shale gas revolution.

The shale gas revolution instrument is determined at the country level. It takes on a value of one for the United States and Canada starting in 2009 (when the shale revolution began to take effect), and is zero in all other countries and time periods. To construct the inventor-specific instrument z_{it}, we take the same approach described in Section 3 for constructing inventor-specific natural gas prices: First, we compute firm-specific values of the instrument as a weighted average of the country-specific instrument, where the weights for each firm depend on the location of their patenting activity. Then, we use these firm-specific values of the instrument to compute the inventor-specific instrument. Here, the weights depend on the share of each inventor's patents that are associated with each firm.

The first-stage estimating equation is identical to the first stage of two-stage least-squares. However, it is not appropriate to use predicted values in place of the potentially endogenous regressor in equation 1 because the model is nonlinear. Instead, we recover the residuals from estimating E.1, $\hat{\tilde{u}}_{it}$, and modify equation 1 to include those residuals:

$$PAT^C_{it} = \exp(\beta_P \ln P_{it-1} + \beta_{\tilde{u}} \hat{\tilde{u}}_{it-1} + \beta_X X_{it-1} + \gamma_t + \eta_i) + u_{it}. \tag{E.2}$$

We estimate this augmented model via Poisson pseudo maximum likelihood. To conduct inference, we use a block bootstrap of this two-step procedure at the inventor level, sampling inventors 250 times with replacement.

F Alternative Inference Based on Borusyak et al. (2022)

In this appendix, we present results that rely on an alternative approach to inference. As explained in the main text, we cluster standard errors for regressions by unit (i.e., inventor or firm) because we are not aware of any procedures for inference that are robust to correlated residuals among units with similar exposure shares in the context of nonlinear models.

To provide an indication of how the estimated standard errors may change if methods were available to properly account for these correlated residuals, we estimate a series of additional regressions. First, we reproduce our baseline regressions in Panel A of Table 1, which are estimated via Poisson pseudo maximum likelihood. This model takes the form:

$$PAT_{it}^{C} = \exp(\beta_P \ln P_{it-1} + \beta_X X_{it-1} + \gamma_t + \eta_i) + u_{it}. \tag{F.1}$$

Second, we use ordinary least squares to estimate a linear model that is analogous to the baseline exponential mean model. This model takes the form:

$$\ln\left(0.01 + PAT_{it}^{C}\right) = \beta_P' \ln P_{it-1} + \beta_X' X_{it-1} + \gamma_t' + \eta_i' + u_{it}'. \tag{F.2}$$

The outcome variable for these models is arbitrarily defined to be the natural logarithm of 0.01 plus the patent count, rather than the log of the patent count, due to the presence of zeros in the patent count data. We use this modification because it treats large patent counts similarly to the implicit log transformation in the exponential mean model used for our main specifications. While the coefficients are no longer directly interpretable as elasticities, estimating a model with this transformation via ordinary least squares yields coefficient estimates similar in magnitude to our baseline exponential mean model estimated via Poisson pseudo maximum likelihood. That said, the focus of this analysis is on the standard errors produced by different estimation methods, not the coefficients themselves.

Third and finally, we follow the methods introduced by Borusyak et al. (2022) to estimate an analogous "shock-level" linear regression at the country level rather than at the inventor level. To do so, we first construct exposure-weighted averages of the residuals from a projection of the outcome and treatment variables, $\ln\left(0.01 + PAT_{it}^{C}\right)$ and $\ln P_{it-1}$, on the nuisance parameters in equation F.2. We use the resulting country-year data to estimate the relationship between patenting and natural gas prices using the equation

$$\overline{\ln\left(0.01 + PAT^{C}\right)}_{ct}^{\perp} = \beta_P' \overline{\ln P}_{ct-1}^{\perp} + q_{ct-1}^{T}\delta + \overline{u}_{it}^{\perp}, \tag{F.3}$$

where the notation follows Borusyak et al. (2022).[3] The variable q_{ct-1}^{T} denotes any country-level control variables that are included in shift-share form in the control vector used to compute the other variables in the regression.[4] We estimate this equation by instrumental variables, using observed

3. In brief, $v_{it}^{\perp}$ denotes the residual from a projection of a variable $v_{it}^{\perp}$ on the control vector X_{it-1} and all fixed effects from equation F.2, and $\overline{v}_{ct}$ denotes the exposure-weighted average of an inventor-level variable v_{it}. See Borusyak et al. (2022) for more details.

4. These variables are GDP per capita, public RD&D spending on all energy technologies, public RD&D spending on low-carbon energy technologies, and year fixed effects. Inventor fixed effects and tenure fixed effects are also included in the regressions used to compute the shock-level variables in equation F.3, but they are excluded from q_{ct-1} as prescribed by Borusyak et al. (2022), because they are inventor-level controls rather than country-level controls.

country-year natural gas prices, $\ln P_{ct-1}$, to instrument for their transformed shift-share equivalents, $\overline{\ln P}^{\perp}_{ct-1}$. The regression is weighted by each country's average exposure across inventors. Finally, standard errors are clustered by country.[5]

Tables F.1 and F.2 presents the results of this analysis. In Table F.1, Panel A reproduces the PPML results from Panel A of Table 1 in the main text. Panel B contains results for the $\ln\left(0.01+PAT^{C}_{it}\right)$ approach as shown in Equation F.2. The coefficients are not directly interpretable as elasticities, and are no longer of direct interest. Panel C contains results for the Borusyak et al. (2022)'s approach, as shown in Equation F.3.

Table F.1: Main Results with Alternative Inference Methods

	Count of Clean Patent Families					
	Simple Count		Citation-Weighted		Coinventor-Weighted	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Poisson estimates						
Prices (log, t-1)	0.495	0.396	0.582	0.451	0.458	0.374
	(0.038)	(0.039)	(0.048)	(0.048)	(0.049)	(0.049)
Standard errors clustered by	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Number of clusters	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
Pseudo-R2	0.291	0.292	0.373	0.375	0.265	0.266
Panel B: OLS estimates						
Prices (log, t-1)	0.640	0.416	0.685	0.459	0.494	0.323
	(0.026)	(0.026)	(0.024)	(0.025)	(0.021)	(0.022)
Standard errors clustered by	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Number of clusters	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
Adjusted R2	0.179	0.183	0.189	0.194	0.179	0.183
Panel C: Shock-level estimates						
Prices (log, t-1)	0.653	0.401	0.754	0.558	0.498	0.305
	(0.166)	(0.093)	(0.097)	(0.065)	(0.144)	(0.086)
Year fixed effects (shock level)	X	X	X	X	X	X
Country-year covariates (shock level)	X	X	X	X	X	X
Standard errors clustered by	Country	Country	Country	Country	Country	Country
Number of clusters	27	27	27	27	27	27
Observations	342	342	342	342	342	342
Covariates included in all panels						
Year fixed effects	X	X	X	X	X	X
Inventor fixed effects	X	X	X	X	X	X
Tenure fixed effects		X		X		X
Country-year covariates	X	X	X	X	X	X

5. All implementation details, including weighting and clustering, follow Borusyak et al. (2022).

Three things stand out in the comparison between Panels B and C. First, the standard errors in Panel C are larger than those in Panel B. This is because the approach in Panel C better accounts for the possibility of correlated residuals among units with similar exposure shares. Second, all of the estimates in Panel C remain statistically significant at conventional levels despite the larger standard errors. Third and finally, the coefficients are slightly different. In principle, the approach in Panel C of Table F.1 should be able to replicate the coefficient estimates in Panel B, given the equivalence results in Borusyak et al. (2022). As it turns out, implementing the methods from Borusyak et al. (2022) in our case is complicated slightly by missing data. For a small number of countries and years, we do not observe data on RD&D spending. In our main analysis, we circumvent this data limitation by modifying the weights on a variable-specific basis to omit these missing observations from the computation of inventor-level exposure variables. As a result, the weights we use to determine inventor-level exposures vary slightly.[6] Consequently, this results in a minor variation in the coefficients obtained from estimating the model at the inventor-level and estimating the "shock-level" model at the country-level following Borusyak et al. (2022).

To confirm that we can replicate the inventor-level coefficients using this country-level approach to estimation and inference, we also estimate a set of restricted models that omit covariates that vary over both countries and time. Specifically, the three country-level covariates we include in Table F.1 but exclude from Table F.2 are GDP per capita, public RD&D spending on all energy technologies, public RD&D spending on low-carbon energy technologies.

Table F.2 contains the estimates from these modified specifications. The coefficients in Panel A of Table F.2 are slightly larger than their counterparts in Panel A of Table F.1 due to the omission of these three covariates. However, this analysis is focused on inference, and the standard errors are very similar in magnitude in both versions of Panel A. Focusing on Panels B and C, three things stand out in the comparison between Tables F.1 and F.2. First, the identical coefficients within each column of Panels B and C of Table F.2 confirm that our "shock-level" estimation using country-level data successfully reproduces the shift-share estimates derived from inventor-level data. This is consistent with the equivalence results in Borusyak et al. (2022). Second, as before, the standard errors in Panel C are larger than those in Panel B, but they remain statistically significant at conventional levels. Third and finally, the standard errors in Panel C of Table F.2 are similar to or smaller than their counterparts in Table F.1.

In summary, these results suggest that the standard errors in our primary analysis may exhibit a downward bias due to the fact that clustering the standard errors in inventor-level regressions does not fully account for the possibility of correlated residuals among inventors with similar exposure shares. Yet the magnitude of this bias may be small given that all the estimates in Panel C of F.1 and F.2 remain statistically significant. On net, these results do not signal that the main results of the paper hinge on the shortcomings of current inference methods available for nonlinear models of the type we estimate.

6. This is despite the fact that we use constant exposure shares based on pre-period patenting activity in our analysis. The slight variation in inventor-level exposure shares comes from missing data for individual regressors at the country level (e.g., RD&D spending for a given country in a given year), not a source of endogeneity in the construction of exposures at the inventor level (e.g., from using exposure shares based on contemporaneous patenting activity).

Table F.2: Main Results with Alternative Inference Methods

	Count of Clean Patent Families					
	Simple Count		Citation-Weighted		Coinventor-Weighted	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Poisson estimates						
Prices (log, t-1)	0.598	0.502	0.824	0.669	0.505	0.420
	(0.037)	(0.038)	(0.049)	(0.050)	(0.045)	(0.047)
Standard errors clustered by	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Number of clusters	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
Pseudo-R2	0.290	0.291	0.372	0.374	0.265	0.265
Panel B: OLS estimates						
Prices (log, t-1)	0.681	0.424	0.755	0.499	0.523	0.327
	(0.025)	(0.026)	(0.024)	(0.025)	(0.020)	(0.021)
Standard errors clustered by	Inventor	Inventor	Inventor	Inventor	Inventor	Inventor
Number of clusters	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
Adjusted R2	0.178	0.183	0.188	0.194	0.179	0.183
Panel C: Shock-level estimates						
Prices (log, t-1)	0.681	0.424	0.755	0.499	0.523	0.327
	(0.153)	(0.053)	(0.084)	(0.071)	(0.136)	(0.051)
Year fixed effects (shock level)	X	X	X	X	X	X
Country-year covariates (shock level)						
Standard errors clustered by	Country	Country	Country	Country	Country	Country
Number of clusters	31	31	31	31	31	31
Observations	428	428	428	428	428	428
Covariates included in all panels						
Year fixed effects	X	X	X	X	X	X
Inventor fixed effects	X	X	X	X	X	X
Tenure fixed effects		X		X		X
Country-year covariates						

G Robustness of Incumbent Patenting Results

G.1 Main Results Showing All Controls

Table G.1: Baseline estimates showing all controls

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.495***	0.396***	0.582***	0.451***	0.458***	0.374***
	(0.038)	(0.039)	(0.048)	(0.048)	(0.049)	(0.049)
GDP per capita (log, t-1)	3.381***	4.111***	5.712***	6.399***	1.791***	2.543***
	(0.389)	(0.373)	(0.405)	(0.392)	(0.477)	(0.444)
Energy RD&D (log, t-1)	-0.068**	-0.063**	-0.046	-0.033	-0.014	-0.008
	(0.030)	(0.031)	(0.040)	(0.041)	(0.036)	(0.037)
Low-Carbon RD&D (log, t-1)	-0.095**	0.004	-0.402***	-0.204***	-0.047	0.033
	(0.037)	(0.036)	(0.049)	(0.048)	(0.042)	(0.040)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
Pseudo-R2	0.291	0.292	0.373	0.375	0.265	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.2: IV estimates showing all controls

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.523***	0.308***	0.871***	0.596***	0.412***	0.211***
	(0.058)	(0.060)	(0.077)	(0.077)	(0.071)	(0.072)
GDP per capita (log, t-1)	3.34***	4.26***	5.09***	6.09***	1.87***	2.83***
	(0.125)	(0.127)	(0.150)	(0.151)	(0.177)	(0.178)
Energy RD&D (log, t-1)	-0.065***	-0.073***	0.005	-0.008	-0.018	-0.023
	(0.022)	(0.023)	(0.025)	(0.026)	(0.031)	(0.032)
Low-Carbon RD&D (log, t-1)	-0.090***	-0.007	-0.332***	-0.179***	-0.052	0.021
	(0.024)	(0.025)	(0.028)	(0.028)	(0.033)	(0.033)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Inventor Clusters (SEs)	101,839	101,839	101,839	101,839	101,839	101,839
Observations	728,565	728,565	728,565	728,565	728,565	728,565
First-stage F-statistic	163	163	163	163	163	163

Dependent variable: Number of Renewable/Nuclear docdb patent families .

Poisson pseudo-maximum likelihood. Bootstrapped (N=250) standard errors in parentheses.

Table G.3: Distributed lags estimates showing all controls

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.191***	0.184***	0.344***	0.351***	0.207***	0.189***
	(0.046)	(0.046)	(0.059)	(0.058)	(0.053)	(0.053)
Prices (log, t-2)	0.173***	0.098**	0.131**	0.025	0.295***	0.218***
	(0.045)	(0.045)	(0.058)	(0.058)	(0.055)	(0.054)
Prices (log, t-3)	0.169***	0.138***	0.076	0.033	0.061	0.034
	(0.045)	(0.045)	(0.051)	(0.052)	(0.053)	(0.053)
L.GDP per capita (log, k$)	3.846***	4.310***	4.562***	5.157***	3.934**	4.492***
	(1.238)	(1.160)	(0.803)	(0.757)	(1.583)	(1.468)
L2.GDP per capita (log, k$)	0.104	0.461	1.654***	2.067***	-0.642	-0.187
	(0.753)	(0.712)	(0.541)	(0.522)	(1.030)	(0.958)
L3.GDP per capita (log, k$)	-0.251	-0.223	1.945***	1.902***	-1.667***	-1.583***
	(0.368)	(0.354)	(0.381)	(0.380)	(0.430)	(0.420)
L.Energy RD&D (log, m$)	-0.187***	-0.141***	-0.118**	-0.039	-0.132**	-0.097*
	(0.050)	(0.050)	(0.059)	(0.060)	(0.052)	(0.053)
L2.Energy RD&D (log, m$)	-0.246***	-0.212***	0.046	0.113*	-0.194***	-0.170***
	(0.044)	(0.045)	(0.059)	(0.059)	(0.051)	(0.051)
L3.Energy RD&D (log, m$)	-0.092***	-0.074**	0.078*	0.111***	-0.140***	-0.123***
	(0.033)	(0.033)	(0.042)	(0.042)	(0.039)	(0.038)
L.Low-Carbon RD&D (log, m$)	0.036	0.133**	-0.326***	-0.172**	0.036	0.131**
	(0.059)	(0.059)	(0.070)	(0.070)	(0.064)	(0.063)
L2.Low-Carbon RD&D (log, m$)	0.164***	0.203***	-0.203***	-0.142**	0.228***	0.262***
	(0.042)	(0.043)	(0.058)	(0.059)	(0.050)	(0.050)
L3.Low-Carbon RD&D (log, m$)	-0.026	-0.005	-0.138***	-0.103**	0.058	0.082**
	(0.038)	(0.038)	(0.046)	(0.046)	(0.041)	(0.041)
Cumulative Effect	0.534***	0.420***	0.551***	0.410***	0.564***	0.441***
	(0.050)	(0.052)	(0.065)	(0.066)	(0.059)	(0.062)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	80,795	80,795	80,795	80,795	80,795	80,795
Observations	572,195	572,195	572,195	572,195	572,195	572,195
Pseudo-R2	0.294	0.295	0.370	0.372	0.267	0.268

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.2 Alternative Outcome: Broader Definition of Clean Patenting

Table G.4: Main Results with Clean Patenting as Outcome

	Count of Clean Patent Families					
	Simple Count		Citation-Weighted		Coinventor-Weighted	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline Poisson estimates						
Prices (log, t-1)	0.321	0.243	0.370	0.262	0.309	0.238
	(0.024)	(0.025)	(0.035)	(0.035)	(0.026)	(0.027)
Inventors	192,106	192,106	192,106	192,106	192,106	192,106
Observations	1,443,210	1,443,210	1,443,210	1,443,210	1,443,210	1,443,210
Pseudo-R2	0.340	0.341	0.395	0.397	0.285	0.286
Panel B: Instrumental variable estimates						
Prices (log, t-1)	0.385	0.166	0.707	0.429	0.350	0.137
	(0.042)	(0.044)	(0.059)	(0.060)	(0.042)	(0.044)
Inventors	192,106	192,106	192,106	192,106	192,106	192,106
Observations	1,443,210	1,443,210	1,443,210	1,443,210	1,443,210	1,443,210
First-stage F-statistic	163	163	163	163	163	163
Panel C: Distributed lag estimates						
Cumulative effect (3 lags)	0.346	0.289	0.269	0.199	0.398	0.331
	(0.035)	(0.036)	(0.053)	(0.053)	(0.037)	(0.037)
Inventors	149,983	149,983	149,983	149,983	149,983	149,983
Observations	1,120,566	1,120,566	1,120,566	1,120,566	1,120,566	1,120,566
Pseudo-R2	0.346	0.347	0.398	0.399	0.290	0.291
Year fixed effects	X	X	X	X	X	X
Inventor fixed effects	X	X	X	X	X	X
Tenure fixed effects		X		X		X
Country-year covariates	X	X	X	X	X	X

Note: The dependent variables are the number of clean patent families, either unweighted, weighted by citations, or inversely weighted by the number of inventors, depending on the column. Panels A, B, and C contain estimates of the same parameters using different estimation strategies. Panel A presents estimates of equation 1 estimated via Poisson pseudo-maximum likelihood. Standard errors are clustered by inventor and reported in parentheses. Panel B presents estimates of equation E.2 estimated via the control function approach described in the text, using the shale gas revolution as an instrument for natural gas prices. Standard errors are constructed via block bootstrap of the two-step control function approach, sampling inventors 250 times with replacement. The first-stage F-statistic for the instrumental variable estimates is from estimating equation E.1 at the country-year level rather than the inventor-year level, since the instrument varies at the country level and it thus provides a more conservative assessment of the instrument's strength. Panel C is analogous to Panel A except that the models include three lags of natural gas prices and all other covariates that vary across both countries and time, and the coefficients represent cumulative effects.

G.3 Alternative Outcome: International and Triadic Families

G.3.1 Baseline Definition of Clean

Table G.5: Baseline Poisson Estimates with Alternative Outcome Variables

	(1) Simple Count	(2) Coinventor-Weighted	(3) Citation-Weighted (3y)	(4) Citation-Weighted (5y)	(5) Triadic	(6) Triadic	(7) Granted	(8) Granted	(9) Triadic granted	(10) Triadic granted	(11) More than 2 countries	(12) More than 2 countries	(13) More than 2 OECD	(14) More than 2 OECD
Prices (log, t-1)	0.396***	0.374***	0.451***	0.382***	0.099	-0.123	0.231***	0.227***	-0.001	-0.222	0.419***	0.358***	0.304***	0.227***
	(0.039)	(0.049)	(0.048)	(0.050)	(0.083)	(0.132)	(0.040)	(0.053)	(0.087)	(0.138)	(0.052)	(0.073)	(0.054)	(0.079)
GDP per capita (log, t-1)	4.111***	2.543***	6.399***	7.137***	4.632***	4.426***	4.611***	2.889***	4.929***	4.818***	4.468***	2.922***	4.434***	2.974***
	(0.373)	(0.444)	(0.392)	(0.416)	(0.821)	(0.868)	(0.333)	(0.341)	(0.846)	(0.898)	(0.482)	(0.511)	(0.490)	(0.523)
Energy RD&D (log, t-1)	-0.063**	-0.008	-0.033	-0.035	-0.157*	-0.217*	-0.124***	-0.058	-0.133	-0.167	0.086*	0.205***	0.027	0.166***
	(0.031)	(0.037)	(0.041)	(0.044)	(0.090)	(0.122)	(0.034)	(0.041)	(0.092)	(0.124)	(0.047)	(0.060)	(0.049)	(0.063)
Low-Carbon RD&D (log, t-1)	0.004	0.033	-0.204***	-0.237***	-0.484***	-0.333**	-0.029	0.009	-0.551***	-0.437***	-0.309***	-0.318***	-0.271***	-0.272***
	(0.036)	(0.040)	(0.048)	(0.052)	(0.110)	(0.134)	(0.037)	(0.043)	(0.113)	(0.136)	(0.056)	(0.069)	(0.058)	(0.072)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Coinventor-Weighted		X				X		X		X		X		X
Inventor Clusters (SEs)	101,839	101,839	101,839	101,839	26,038	26,038	83,452	83,452	24,399	24,399	60,699	60,699	53,180	53,180
Observations	728,565	728,565	728,565	728,565	200,635	200,635	601,408	601,408	188,609	188,609	439,944	439,944	394,785	394,785
Pseudo-R2	0.292	0.266	0.375	0.392	0.210	0.214	0.259	0.239	0.204	0.210	0.235	0.229	0.226	0.223

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Note: This table show specifications similar to Panel a of Table 1 in the main text but using different left-hand side variables. Columns 1, 2, and 3 are the same as Column 2, 6, and 4 in Panel a of Table 1. The other columns present results for the count of clean families that are "triadic" (i.e., filed at the USPTO, EPO and JPO), granted in at least one jurisdiction, filed in more than two countries, or filed in more than two OECD countries. Most results are consistent with the baseline results shown in Table 1 except for specifications using triadic families as outcome variables. Triadic families are not very common in our dataset. As shown in Table D.1, the number of clean families for the average clean incumbent is 0.5, but it is only 0.1 for triadic families. The standard deviation is also much lower, and the 90th percentile is 0.

Table G.6: Distributed Lag Estimates with Alternative Outcome Variables

	(1) Simple Count	(2) Coinventor-Weighted	(3) Citation-Weighted (3y)	(4) Citation-Weighted (5y)	(5) Triadic	(6) Triadic	(7) Granted	(8) Granted	(9) Triadic granted	(10) Triadic granted	(11) More than 2 countries	(12) More than 2 countries	(13) More than 2 OECD	(14) More than 2 OECD
Prices (log, t-1)	0.184***	0.189***	0.351***	0.242***	0.235**	0.210*	0.100**	0.101*	0.083	0.032	0.314***	0.318***	0.279***	0.262***
	(0.046)	(0.053)	(0.058)	(0.061)	(0.099)	(0.123)	(0.049)	(0.060)	(0.103)	(0.128)	(0.062)	(0.074)	(0.066)	(0.080)
Prices (log, t-2)	0.098**	0.218***	0.025	0.005	-0.167*	-0.311**	-0.082*	0.028	-0.187*	-0.318**	0.181***	0.090	0.120*	0.040
	(0.045)	(0.054)	(0.058)	(0.059)	(0.098)	(0.122)	(0.047)	(0.057)	(0.103)	(0.129)	(0.060)	(0.074)	(0.065)	(0.080)
Prices (log, t-3)	0.138***	0.034	0.033	0.078	-0.265***	-0.284**	0.201***	0.155***	-0.229**	-0.201*	-0.021	0.013	-0.115*	-0.072
	(0.045)	(0.053)	(0.052)	(0.054)	(0.089)	(0.113)	(0.046)	(0.053)	(0.091)	(0.118)	(0.056)	(0.067)	(0.060)	(0.072)
L.GDP per capita (log, k$)	4.310***	4.492***	5.157***	5.005***	1.697*	2.470*	3.379***	2.984***	1.722*	2.680**	3.087***	2.756***	3.081***	2.969***
	(1.160)	(1.468)	(0.757)	(0.664)	(0.962)	(1.293)	(0.421)	(0.512)	(1.001)	(1.363)	(0.568)	(0.730)	(0.592)	(0.740)
L2.GDP per capita (log, k$)	0.461	-0.187	2.067***	2.621***	1.897**	1.677*	1.349***	1.107**	1.709**	1.714*	1.766***	1.208**	1.697***	1.083*
	(0.712)	(0.958)	(0.522)	(0.478)	(0.763)	(0.986)	(0.383)	(0.490)	(0.767)	(1.041)	(0.483)	(0.590)	(0.501)	(0.604)
L3.GDP per capita (log, k$)	-0.223	-1.583***	1.902***	2.645***	4.812***	3.321***	0.672*	-0.705	5.299***	3.372***	1.843***	1.067*	2.028***	1.148**
	(0.354)	(0.420)	(0.380)	(0.398)	(0.713)	(0.944)	(0.361)	(0.512)	(0.741)	(0.993)	(0.456)	(0.546)	(0.469)	(0.571)
L.Energy RD&D (log, m$)	-0.141***	-0.097*	-0.039	-0.028	0.043	0.010	-0.127**	-0.110*	0.090	0.043	0.026	0.187**	-0.009	0.152*
	(0.050)	(0.053)	(0.060)	(0.063)	(0.127)	(0.167)	(0.051)	(0.057)	(0.130)	(0.171)	(0.068)	(0.086)	(0.070)	(0.090)
L2.Energy RD&D (log, m$)	-0.212***	-0.170***	0.113*	0.145**	-0.000	0.084	-0.217***	-0.169***	-0.037	0.077	0.226***	0.287***	0.150**	0.225***
	(0.045)	(0.051)	(0.059)	(0.063)	(0.134)	(0.151)	(0.044)	(0.051)	(0.136)	(0.154)	(0.069)	(0.080)	(0.072)	(0.084)
L3.Energy RD&D (log, m$)	-0.074**	-0.123***	0.111***	0.122**	0.245***	0.195*	-0.023	-0.040	0.196**	0.174*	0.196***	0.172***	0.151***	0.152***
	(0.033)	(0.038)	(0.042)	(0.050)	(0.091)	(0.101)	(0.034)	(0.039)	(0.094)	(0.105)	(0.048)	(0.057)	(0.050)	(0.058)
L.Low-Carbon RD&D (log, m$)	0.133**	0.131**	-0.172**	-0.235***	-0.704***	-0.566***	0.054	0.100	-0.817***	-0.680***	-0.324***	-0.392***	-0.291***	-0.349***
	(0.059)	(0.063)	(0.070)	(0.075)	(0.154)	(0.178)	(0.056)	(0.062)	(0.159)	(0.181)	(0.079)	(0.099)	(0.082)	(0.103)
L2.Low-Carbon RD&D (log, m$)	0.203***	0.262***	-0.142**	-0.162**	-0.126	-0.170	0.173***	0.167***	-0.084	-0.194	-0.246***	-0.225***	-0.199***	-0.179**
	(0.043)	(0.050)	(0.059)	(0.064)	(0.128)	(0.150)	(0.044)	(0.051)	(0.130)	(0.155)	(0.066)	(0.076)	(0.069)	(0.080)
L3.Low-Carbon RD&D (log, m$)	-0.005	0.082**	-0.103**	-0.119**	-0.490***	-0.309***	-0.127***	-0.061	-0.496***	-0.315***	-0.197***	-0.158***	-0.204***	-0.155**
	(0.038)	(0.041)	(0.046)	(0.054)	(0.092)	(0.108)	(0.038)	(0.042)	(0.095)	(0.113)	(0.051)	(0.060)	(0.052)	(0.062)
Cumulative Effect	0.420***	0.441***	0.410***	0.325***	-0.198*	-0.385***	0.220***	0.284***	-0.333***	-0.488***	0.474***	0.421***	0.284***	0.230**
	(0.052)	(0.062)	(0.066)	(0.069)	(0.103)	(0.133)	(0.054)	(0.068)	(0.106)	(0.135)	(0.067)	(0.084)	(0.070)	(0.090)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Coinventor-Weighted		X				X		X		X		X		X
Inventor Clusters (SEs)	80,795	80,795	80,795	80,795	20,304	20,304	66,110	66,110	18,962	18,962	47,686	47,686	41,505	41,505
Observations	572,195	572,195	572,195	572,195	156,331	156,331	474,218	474,218	146,339	146,339	344,973	344,973	307,974	307,974
Pseudo-R2	0.295	0.268	0.372	0.387	0.210	0.214	0.261	0.239	0.204	0.210	0.235	0.228	0.226	0.222

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Note: This table show specifications similar to Table G.5 but with three lags of natural gas prices and other variables that vary by country and year.

G.3.2 Broader Definition of Clean

Table G.7: Baseline Poisson Estimates with Alternative Outcome Variables

	(1) Simple Count	(2) Coinventor-Weighted	(3) Citation-Weighted (3y)	(4) Citation-Weighted (5y)	(5) Triadic	(6) Triadic	(7) Granted	(8) Granted	(9) Triadic granted	(10) Triadic granted	(11) More than 2 countries	(12) More than 2 countries	(13) More than 2 OECD	(14) More than 2 OECD
Prices (log, t-1)	0.243***	0.238***	0.262***	0.231***	0.360***	0.250***	0.193***	0.204***	0.323***	0.208***	0.353***	0.307***	0.305***	0.216***
	(0.025)	(0.027)	(0.035)	(0.037)	(0.049)	(0.070)	(0.027)	(0.031)	(0.049)	(0.073)	(0.033)	(0.041)	(0.034)	(0.043)
GDP per capita (log, t-1)	5.023***	3.989***	6.728***	7.317***	4.720***	4.889***	4.932***	4.044***	5.020***	5.227***	4.281***	3.804***	4.291***	3.884***
	(0.220)	(0.208)	(0.266)	(0.277)	(0.488)	(0.502)	(0.228)	(0.226)	(0.499)	(0.516)	(0.306)	(0.320)	(0.312)	(0.330)
Energy RD&D (log, t-1)	-0.082***	0.011	-0.064**	-0.080***	-0.160***	-0.157***	-0.136***	-0.048*	-0.180***	-0.179***	-0.023	0.062*	-0.099***	-0.008
	(0.022)	(0.023)	(0.026)	(0.028)	(0.045)	(0.053)	(0.023)	(0.026)	(0.045)	(0.051)	(0.029)	(0.034)	(0.031)	(0.036)
Low-Carbon RD&D (log, t-1)	0.000	-0.056**	-0.193***	-0.242***	-0.587***	-0.576***	-0.083***	-0.154***	-0.635***	-0.637***	-0.382***	-0.504***	-0.371***	-0.480***
	(0.025)	(0.025)	(0.032)	(0.033)	(0.057)	(0.063)	(0.027)	(0.029)	(0.058)	(0.064)	(0.036)	(0.041)	(0.037)	(0.042)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Coinventor-Weighted		X				X		X		X		X		X
Inventor Clusters (SEs)	192,106	192,106	192,106	192,106	60,862	60,862	162,486	162,486	57,499	57,499	124,219	124,219	111,290	111,290
Observations	1,443,210	1,443,210	1,443,210	1,443,210	505,533	505,533	1,239,641	1,239,641	479,501	479,501	959,866	959,866	880,361	880,361
Pseudo-R2	0.341	0.286	0.397	0.407	0.212	0.195	0.300	0.249	0.207	0.191	0.257	0.227	0.255	0.225

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Note: This table show specifications similar to Table G.5 but for the broader definition of clean.

Table G.8: Distributed Lag Estimates with Alternative Outcome Variables

	(1) Simple Count	(2) Coinventor-Weighted	(3) Citation-Weighted (3y)	(4) Citation-Weighted (5y)	(5) Triadic	(6) Triadic	(7) Granted	(8) Granted	(9) Triadic granted	(10) Triadic granted	(11) More than 2 countries	(12) More than 2 countries	(13) More than 2 OECD	(14) More than 2 OECD
Prices (log, t-1)	-0.108***	-0.090***	0.038	-0.044	0.032	0.012	-0.173***	-0.160***	-0.078	-0.098	0.021	-0.007	0.003	-0.055
	(0.033)	(0.035)	(0.064)	(0.063)	(0.071)	(0.080)	(0.036)	(0.039)	(0.071)	(0.080)	(0.046)	(0.050)	(0.048)	(0.053)
Prices (log, t-2)	0.165***	0.191***	0.114**	0.080	0.078	0.058	0.115***	0.149***	0.071	0.062	0.244***	0.256***	0.225***	0.228***
	(0.029)	(0.032)	(0.053)	(0.054)	(0.065)	(0.075)	(0.032)	(0.036)	(0.065)	(0.076)	(0.041)	(0.046)	(0.044)	(0.050)
Prices (log, t-3)	0.232***	0.230***	0.046	0.144**	0.010	0.015	0.275***	0.288***	0.050	0.049	0.160***	0.179***	0.115***	0.136***
	(0.029)	(0.032)	(0.056)	(0.058)	(0.061)	(0.071)	(0.032)	(0.035)	(0.062)	(0.073)	(0.038)	(0.044)	(0.041)	(0.047)
L.GDP per capita (log, k$)	2.830***	2.474***	4.171***	4.392***	1.553***	1.659**	2.861***	2.413***	1.631***	1.769**	2.664***	2.226***	2.706***	2.454***
	(0.292)	(0.332)	(0.321)	(0.326)	(0.591)	(0.746)	(0.283)	(0.321)	(0.603)	(0.778)	(0.368)	(0.431)	(0.383)	(0.448)
L2.GDP per capita (log, k$)	1.988***	1.792***	2.511***	2.731***	2.161***	2.494***	1.949***	1.911***	2.137***	2.685***	1.348***	1.598***	1.362***	1.478***
	(0.245)	(0.289)	(0.277)	(0.280)	(0.464)	(0.587)	(0.252)	(0.303)	(0.475)	(0.622)	(0.315)	(0.371)	(0.332)	(0.390)
L3.GDP per capita (log, k$)	0.916***	0.404*	2.236***	2.648***	3.540***	2.982***	1.127***	0.678**	3.864***	3.013***	1.864***	1.678***	1.863***	1.637***
	(0.215)	(0.234)	(0.278)	(0.287)	(0.437)	(0.514)	(0.246)	(0.284)	(0.451)	(0.538)	(0.297)	(0.323)	(0.316)	(0.344)
L.Energy RD&D (log, m$)	-0.082**	0.008	0.030	0.036	-0.129*	-0.148	-0.109***	-0.023	-0.196**	-0.215**	-0.080*	0.007	-0.140***	-0.048
	(0.035)	(0.036)	(0.054)	(0.056)	(0.077)	(0.090)	(0.037)	(0.041)	(0.079)	(0.090)	(0.049)	(0.056)	(0.051)	(0.059)
L2.Energy RD&D (log, m$)	-0.098***	-0.050	0.002	0.045	-0.166**	-0.095	-0.121***	-0.059*	-0.214***	-0.143*	0.033	0.132***	-0.041	0.056
	(0.032)	(0.032)	(0.041)	(0.042)	(0.069)	(0.077)	(0.033)	(0.035)	(0.071)	(0.079)	(0.044)	(0.049)	(0.046)	(0.051)
L3.Energy RD&D (log, m$)	0.053**	-0.005	0.092***	0.121***	0.094*	0.057	0.098***	0.048*	0.078	0.046	0.170***	0.148***	0.111***	0.095**
	(0.023)	(0.024)	(0.034)	(0.036)	(0.053)	(0.061)	(0.023)	(0.025)	(0.055)	(0.062)	(0.033)	(0.036)	(0.034)	(0.038)
L.Low-Carbon RD&D (log, m$)	0.078**	0.001	-0.226***	-0.317***	-0.488***	-0.425***	-0.029	-0.101**	-0.510***	-0.451***	-0.283***	-0.415***	-0.286***	-0.394***
	(0.038)	(0.039)	(0.057)	(0.061)	(0.087)	(0.100)	(0.042)	(0.045)	(0.091)	(0.103)	(0.056)	(0.064)	(0.058)	(0.068)
L2.Low-Carbon RD&D (log, m$)	0.068**	0.073**	-0.062	-0.095	-0.315***	-0.323***	0.026	-0.014	-0.338***	-0.343***	-0.226***	-0.299***	-0.188***	-0.251***
	(0.032)	(0.035)	(0.057)	(0.059)	(0.071)	(0.082)	(0.033)	(0.037)	(0.073)	(0.085)	(0.044)	(0.049)	(0.046)	(0.052)
L3.Low-Carbon RD&D (log, m$)	-0.188***	-0.092***	-0.290***	-0.336***	-0.490***	-0.384***	-0.302***	-0.231***	-0.485***	-0.380***	-0.291***	-0.241***	-0.293***	-0.239***
	(0.025)	(0.026)	(0.031)	(0.034)	(0.053)	(0.062)	(0.025)	(0.027)	(0.055)	(0.063)	(0.036)	(0.038)	(0.037)	(0.040)
Cumulative Effect	0.289***	0.331***	0.199***	0.180***	0.120*	0.085	0.217***	0.277***	0.043	0.013	0.425***	0.427***	0.342***	0.309***
	(0.036)	(0.037)	(0.053)	(0.055)	(0.068)	(0.082)	(0.038)	(0.041)	(0.068)	(0.081)	(0.048)	(0.052)	(0.048)	(0.055)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Coinventor-Weighted		X				X		X		X		X		X
Inventor Clusters (SEs)	149,983	149,983	149,983	149,983	46,586	46,586	126,588	126,588	43,876	43,876	96,108	96,108	85,644	85,644
Observations	1,120,566	1,120,566	1,120,566	1,120,566	386,059	386,059	963,897	963,897	364,739	364,739	742,102	742,102	677,469	677,469
Pseudo-R2	0.347	0.291	0.399	0.408	0.211	0.194	0.305	0.253	0.206	0.190	0.259	0.228	0.256	0.226

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Note: This table show specifications similar to Table G.5 but for the broader definition of clean and with three lags of natural gas prices and other variables that vary by country and year.

G.4 Robustness Check: Truncated Inventor Panel

Here we implement a robustness check where we arbitrarily truncate each inventor's time series to half of its original length. For example, if we observe an inventor filing their first patent in 2000 and their last patent in 2005 (i.e., total length of six years), we would keep observations for this inventor only up to and including 2002.

This robustness check is useful because, although we directly observe when inventors produce their first patent, we do not know for sure when they "exit." We can, therefore, only safely input zeros for years when inventors do not file patents when these years come in between the first and last filing years of the inventor. This robustness check shows that our results are not sensitive to the timing of an inventors' last observed patent.

G.4.1 Baseline Definition of Clean

Table G.9: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.446***	0.450***	0.573***	0.577***	0.480***	0.483***
	(0.093)	(0.091)	(0.127)	(0.126)	(0.118)	(0.117)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	26,072	26,072	26,072	26,072	26,072	26,072
Observations	95,307	95,307	95,307	95,307	95,307	95,307
Pseudo-R2	0.310	0.311	0.443	0.443	0.289	0.289

Dependent variable: Number of Renewable/Nuclear docdb patent families (citation weighted or not).

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.10: Distributed Lag Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.441***	0.448***	0.538***	0.550***	0.724***	0.727***
	(0.144)	(0.144)	(0.184)	(0.184)	(0.168)	(0.168)
Prices (log, t-2)	0.070	0.067	0.208	0.192	0.317*	0.313*
	(0.143)	(0.143)	(0.214)	(0.212)	(0.172)	(0.172)
Prices (log, t-3)	0.172	0.172	0.362*	0.362*	-0.257	-0.256
	(0.137)	(0.137)	(0.195)	(0.195)	(0.162)	(0.162)
Cumulative Effect	0.683***	0.687***	1.108***	1.103***	0.784***	0.783***
	(0.200)	(0.200)	(0.303)	(0.300)	(0.223)	(0.222)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	13,516	13,516	13,516	13,516	13,516	13,516
Observations	45,162	45,162	45,162	45,162	45,162	45,162
Pseudo-R2	0.312	0.313	0.451	0.452	0.286	0.287

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.4.2 Broader Definition of Clean

Table G.11: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.208***	0.218***	0.204**	0.223***	0.076	0.080
	(0.059)	(0.059)	(0.082)	(0.081)	(0.068)	(0.067)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	54,890	54,890	54,890	54,890	54,890	54,890
Observations	211,496	211,496	211,496	211,496	211,496	211,496
Pseudo-R2	0.363	0.364	0.440	0.441	0.307	0.307

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families (citation weighted or not).

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.12: Distributed Lag Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.185**	0.196**	0.153	0.175	0.251**	0.256**
	(0.094)	(0.094)	(0.135)	(0.135)	(0.105)	(0.105)
Prices (log, t-2)	0.083	0.081	0.119	0.117	0.139	0.139
	(0.091)	(0.090)	(0.126)	(0.126)	(0.102)	(0.101)
Prices (log, t-3)	0.030	0.041	0.070	0.076	-0.200**	-0.190*
	(0.091)	(0.091)	(0.127)	(0.127)	(0.102)	(0.102)
Cumulative Effect	0.297**	0.317**	0.342*	0.368**	0.189	0.206
	(0.127)	(0.126)	(0.184)	(0.183)	(0.142)	(0.142)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	28,173	28,173	28,173	28,173	28,173	28,173
Observations	99,253	99,253	99,253	99,253	99,253	99,253
Pseudo-R2	0.375	0.376	0.451	0.452	0.317	0.317

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5 Robustness Check: Alternative Prices

Here, we conduct robustness checks using various measures of exposure to natural gas prices. Details on the construction of these exposure measures can be found in Subsection A.7. Results from Table G.13 to Table G.36 confirm that our baseline findings for incumbents remain consistent across different methods of measuring exposure to natural gas prices.

G.5.1 Baseline Clean Definition and Geographic Weights Based on Energy Patents in Pre-Period

Table G.13: Industry Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.526***	0.536***	0.396***	0.399***	0.551***	0.555***	0.451***	0.453***	0.489***	0.501***	0.374***	0.378***
	(0.042)	(0.042)	(0.039)	(0.039)	(0.055)	(0.056)	(0.048)	(0.049)	(0.052)	(0.052)	(0.049)	(0.050)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,839	101,843	101,839	101,843	101,839	101,843	101,839	101,843	101,839	101,843	101,839	101,843
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,565	728,585	728,565	728,585	728,565	728,585	728,565	728,585	728,565	728,585	728,565	728,585
Pseudo-R2	0.292	0.292	0.292	0.292	0.375	0.375	0.375	0.375	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.14: Electricity Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.270***	0.269***	0.128*	0.133**	0.739***	0.699***	0.623***	0.633***	0.108	0.111	0.009	0.011
	(0.067)	(0.067)	(0.067)	(0.067)	(0.079)	(0.080)	(0.076)	(0.077)	(0.082)	(0.082)	(0.088)	(0.088)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	99,805	99,832	99,805	99,832	99,805	99,832	99,805	99,832	99,805	99,832	99,805	99,832
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	717,659	717,790	717,659	717,790	717,659	717,790	717,659	717,790	717,659	717,790	717,659	717,790
Pseudo-R2	0.293	0.293	0.293	0.293	0.376	0.376	0.376	0.376	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.15: Household Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.368***	0.370***	0.317***	0.317***	0.372***	0.364***	0.323***	0.321***	0.401***	0.404***	0.352***	0.352***
	(0.036)	(0.036)	(0.035)	(0.035)	(0.047)	(0.047)	(0.044)	(0.044)	(0.047)	(0.047)	(0.049)	(0.049)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,854	101,856	101,854	101,856	101,854	101,856	101,854	101,856	101,854	101,856	101,854	101,856
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,783	728,796	728,783	728,796	728,783	728,796	728,783	728,796	728,783	728,796	728,783	728,796
Pseudo-R2	0.292	0.292	0.292	0.292	0.375	0.375	0.375	0.375	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.2 Baseline Clean Definition and Baseline Geographic Weights Based on Energy Patents in All Periods

Table G.16: Industry Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.507***	0.523***	0.378***	0.380***	0.586***	0.602***	0.481***	0.484***	0.441***	0.460***	0.329***	0.331***
	(0.038)	(0.038)	(0.040)	(0.040)	(0.052)	(0.053)	(0.051)	(0.051)	(0.047)	(0.048)	(0.052)	(0.052)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,672	101,745	101,672	101,745	101,672	101,745	101,672	101,745	101,672	101,745	101,672	101,745
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	727,695	727,978	727,695	727,978	727,695	727,978	727,695	727,978	727,695	727,978	727,695	727,978
Pseudo-R2	0.292	0.292	0.292	0.292	0.376	0.376	0.375	0.375	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.17: Electricity Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.277***	0.302***	0.124*	0.115*	0.730***	0.734***	0.661***	0.658***	0.050	0.083	-0.060	-0.070
	(0.062)	(0.062)	(0.069)	(0.069)	(0.074)	(0.076)	(0.078)	(0.079)	(0.073)	(0.074)	(0.086)	(0.086)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	99,441	99,551	99,441	99,551	99,441	99,551	99,441	99,551	99,441	99,551	99,441	99,551
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	715,436	715,965	715,436	715,965	715,436	715,965	715,436	715,965	715,436	715,965	715,436	715,965
Pseudo-R2	0.293	0.293	0.293	0.293	0.376	0.376	0.376	0.376	0.267	0.266	0.267	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.18: Household Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.366***	0.368***	0.320***	0.321***	0.424***	0.427***	0.347***	0.349***	0.369***	0.373***	0.347***	0.349***
	(0.032)	(0.032)	(0.036)	(0.036)	(0.043)	(0.043)	(0.045)	(0.045)	(0.042)	(0.042)	(0.045)	(0.045)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,708	101,762	101,708	101,762	101,708	101,762	101,708	101,762	101,708	101,762	101,708	101,762
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,015	728,226	728,015	728,226	728,015	728,226	728,015	728,226	728,015	728,226	728,015	728,226
Pseudo-R2	0.292	0.292	0.292	0.292	0.375	0.375	0.375	0.375	0.266	0.266	0.375	0.375

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.3 Baseline Clean Definition and Geographic Weights Based on All Patents in All Periods

Table G.19: Industry Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.486***	0.504***	0.375***	0.378***	0.546***	0.566***	0.450***	0.454***	0.431***	0.450***	0.330***	0.332***
	(0.037)	(0.038)	(0.040)	(0.040)	(0.052)	(0.052)	(0.050)	(0.050)	(0.046)	(0.046)	(0.050)	(0.050)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,789	101,838	101,789	101,838	101,789	101,838	101,789	101,838	101,789	101,838	101,789	101,838
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,481	728,673	728,481	728,673	728,481	728,673	728,481	728,673	728,481	728,673	728,481	728,673
Pseudo-R2	0.292	0.292	0.292	0.292	0.376	0.376	0.375	0.375	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.20: Electricity Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.239***	0.258***	0.144**	0.136**	0.665***	0.671***	0.656***	0.656***	0.061	0.081	-0.027	-0.034
	(0.053)	(0.054)	(0.061)	(0.062)	(0.072)	(0.074)	(0.077)	(0.078)	(0.059)	(0.061)	(0.075)	(0.076)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	100,053	100,140	100,053	100,140	100,053	100,140	100,053	100,140	100,053	100,140	100,053	100,140
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	718,875	719,296	718,875	719,296	718,875	719,296	718,875	719,296	718,875	719,296	718,875	719,296
Pseudo-R2	0.293	0.293	0.293	0.293	0.376	0.376	0.376	0.376	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.21: Household Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.356***	0.357***	0.314***	0.314***	0.406***	0.406***	0.326***	0.327***	0.362***	0.365***	0.324***	0.325***
	(0.033)	(0.033)	(0.038)	(0.038)	(0.044)	(0.044)	(0.045)	(0.045)	(0.043)	(0.043)	(0.051)	(0.051)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,824	101,852	101,824	101,852	101,824	101,852	101,824	101,852	101,824	101,852	101,824	101,852
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,787	728,904	728,787	728,904	728,787	728,904	728,787	728,904	728,787	728,904	728,787	728,904
Pseudo-R2	0.292	0.292	0.292	0.292	0.375	0.375	0.375	0.375	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.4 Baseline Clean Definition and Geographic Weights Based on All Patents in Pre-Period

Table G.22: Industry Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.519***	0.540***	0.419***	0.424***	0.544***	0.560***	0.455***	0.461***	0.460***	0.478***	0.356***	0.361***
	(0.041)	(0.042)	(0.040)	(0.040)	(0.056)	(0.057)	(0.050)	(0.050)	(0.051)	(0.052)	(0.050)	(0.050)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,814	101,834	101,814	101,834	101,814	101,834	101,814	101,834	101,814	101,834	101,814	101,834
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,663	728,751	728,663	728,751	728,663	728,751	728,663	728,751	728,663	728,751	728,663	728,751
Pseudo-R2	0.292	0.292	0.292	0.292	0.376	0.376	0.376	0.376	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.23: Electricity Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.259***	0.260***	0.186***	0.184***	0.692***	0.678***	0.616***	0.624***	0.121*	0.122*	0.049	0.045
	(0.054)	(0.056)	(0.059)	(0.059)	(0.074)	(0.075)	(0.071)	(0.072)	(0.062)	(0.064)	(0.068)	(0.069)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	100,159	100,201	100,159	100,201	100,159	100,201	100,159	100,201	100,159	100,201	100,159	100,201
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	719,617	719,775	719,617	719,775	719,617	719,775	719,617	719,775	719,617	719,775	719,617	719,775
Pseudo-R2	0.293	0.293	0.293	0.293	0.376	0.376	0.376	0.376	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.24: Household Prices: Baseline Poisson Estimates for Baseline Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.347***	0.350***	0.315***	0.316***	0.365***	0.364***	0.313***	0.313***	0.365***	0.368***	0.322***	0.324***
	(0.035)	(0.035)	(0.037)	(0.037)	(0.048)	(0.048)	(0.045)	(0.045)	(0.048)	(0.048)	(0.050)	(0.051)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	101,836	101,847	101,836	101,847	101,836	101,847	101,836	101,847	101,836	101,847	101,836	101,847
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	728,927	728,964	728,927	728,964	728,927	728,964	728,927	728,964	728,927	728,964	728,927	728,964
Pseudo-R2	0.292	0.292	0.292	0.292	0.375	0.375	0.375	0.375	0.266	0.266	0.266	0.266

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.5 Broader Clean Definition and Baseline Geographic Weights (Based on Energy Patents in All Periods)

Table G.25: Industry Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.324***	0.324***	0.294***	0.293***	0.314***	0.307***	0.325***	0.324***	0.301***	0.301***	0.262***	0.261***
	(0.026)	(0.026)	(0.026)	(0.027)	(0.041)	(0.041)	(0.038)	(0.038)	(0.028)	(0.028)	(0.029)	(0.029)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	191,936	192,018	191,936	192,018	191,936	192,018	191,936	192,018	191,936	192,018	191,936	192,018
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,442,303	1,442,626	1,442,303	1,442,626	1,442,303	1,442,626	1,442,303	1,442,626	1,442,303	1,442,626	1,442,303	1,442,626
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.26: Electricity Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.433***	0.452***	0.440***	0.434***	0.683***	0.675***	0.839***	0.829***	0.390***	0.411***	0.320***	0.314***
	(0.040)	(0.041)	(0.043)	(0.043)	(0.055)	(0.057)	(0.055)	(0.056)	(0.040)	(0.041)	(0.045)	(0.046)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	189,221	189,358	189,221	189,358	189,221	189,358	189,221	189,358	189,221	189,358	189,221	189,358
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,427,649	1,428,280	1,427,649	1,428,280	1,427,649	1,428,280	1,427,649	1,428,280	1,427,649	1,428,280	1,427,649	1,428,280
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.287	0.287	0.287	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.27: Household Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.248***	0.251***	0.244***	0.245***	0.250***	0.256***	0.264***	0.266***	0.249***	0.253***	0.264***	0.266***
	(0.021)	(0.021)	(0.023)	(0.023)	(0.031)	(0.031)	(0.032)	(0.032)	(0.023)	(0.023)	(0.032)	(0.032)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	191,980	192,041	191,980	192,041	191,980	192,041	191,980	192,041	191,980	192,041	191,980	192,041
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,442,579	1,442,823	1,442,579	1,442,823	1,442,579	1,442,823	1,442,579	1,442,823	1,442,579	1,442,823	1,442,579	1,442,823
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.397	0.397

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.6 Broader Clean Definition and Geographic Weights Based on Energy Patents in Pre-Period

Table G.28: Industry Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.263^{***}	0.264^{***}	0.243^{***}	0.244^{***}	0.231^{***}	0.221^{***}	0.262^{***}	0.261^{***}	0.258^{***}	0.260^{***}	0.238^{***}	0.239^{***}
	(0.027)	(0.027)	(0.025)	(0.025)	(0.041)	(0.042)	(0.035)	(0.035)	(0.029)	(0.029)	(0.027)	(0.027)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	192,106	192,109	192,106	192,109	192,106	192,109	192,106	192,109	192,106	192,109	192,106	192,109
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,443,210	1,443,226	1,443,210	1,443,226	1,443,210	1,443,226	1,443,210	1,443,226	1,443,210	1,443,226	1,443,210	1,443,226
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.29: Electricity Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.289^{***}	0.308^{***}	0.345^{***}	0.349^{***}	0.458^{***}	0.456^{***}	0.661^{***}	0.666^{***}	0.310^{***}	0.331^{***}	0.311^{***}	0.315^{***}
	(0.043)	(0.043)	(0.042)	(0.042)	(0.053)	(0.055)	(0.052)	(0.052)	(0.044)	(0.044)	(0.044)	(0.044)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	189,374	189,413	189,374	189,413	189,374	189,413	189,374	189,413	189,374	189,413	189,374	189,413
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,428,719	1,428,904	1,428,719	1,428,904	1,428,719	1,428,904	1,428,719	1,428,904	1,428,719	1,428,904	1,428,719	1,428,904
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.30: Household Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.209^{***}	0.214^{***}	0.207^{***}	0.208^{***}	0.180^{***}	0.183^{***}	0.207^{***}	0.207^{***}	0.229^{***}	0.233^{***}	0.229^{***}	0.231^{***}
	(0.023)	(0.023)	(0.022)	(0.022)	(0.032)	(0.032)	(0.030)	(0.030)	(0.025)	(0.025)	(0.024)	(0.024)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	192,132	192,134	192,132	192,134	192,132	192,134	192,132	192,134	192,132	192,134	192,132	192,134
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,443,434	1,443,447	1,443,434	1,443,447	1,443,434	1,443,447	1,443,434	1,443,447	1,443,434	1,443,447	1,443,434	1,443,447
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.7 Broader Clean Definition and Geographic Weights Based on All Patents in All Periods

Table G.31: Industry Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.293***	0.292***	0.278***	0.278***	0.288***	0.282***	0.308***	0.306***	0.272***	0.272***	0.247***	0.247***
	(0.025)	(0.025)	(0.026)	(0.026)	(0.040)	(0.041)	(0.037)	(0.037)	(0.027)	(0.027)	(0.028)	(0.028)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	192,095	192,149	192,095	192,149	192,095	192,149	192,095	192,149	192,095	192,149	192,095	192,149
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,443,413	1,443,635	1,443,413	1,443,635	1,443,413	1,443,635	1,443,413	1,443,635	1,443,413	1,443,635	1,443,413	1,443,635
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.32: Electricity Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.376***	0.389***	0.407***	0.401***	0.613***	0.603***	0.802***	0.793***	0.364***	0.374***	0.305***	0.298***
	(0.038)	(0.039)	(0.042)	(0.042)	(0.053)	(0.055)	(0.055)	(0.055)	(0.038)	(0.039)	(0.044)	(0.044)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	190,174	190,269	190,174	190,269	190,174	190,269	190,174	190,269	190,174	190,269	190,174	190,269
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,432,878	1,433,329	1,432,878	1,433,329	1,432,878	1,433,329	1,432,878	1,433,329	1,432,878	1,433,329	1,432,878	1,433,329
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.287	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.33: Household Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1) Simple Count	(2) Simple Count	(3) Simple Count	(4) Simple Count	(5) Citation-Weighted	(6) Citation-Weighted	(7) Citation-Weighted	(8) Citation-Weighted	(9) Coinventor-Weighted	(10) Coinventor-Weighted	(11) Coinventor-Weighted	(12) Coinventor-Weighted
Prices (log, t-1)	0.225***	0.227***	0.228***	0.228***	0.233***	0.238***	0.244***	0.245***	0.229***	0.231***	0.229***	0.230***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.031)	(0.031)	(0.031)	(0.031)	(0.023)	(0.023)	(0.024)	(0.024)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	192,135	192,167	192,135	192,167	192,135	192,167	192,135	192,167	192,135	192,167	192,135	192,167
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,443,660	1,443,804	1,443,660	1,443,804	1,443,660	1,443,804	1,443,660	1,443,804	1,443,660	1,443,804	1,443,660	1,443,804
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.5.8 Broader Clean Definition and Geographic Weights Based on All Patents in Pre-Period

Table G.34: Industry Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Simple Count	Simple Count	Simple Count	Simple Count	Citation-Weighted	Citation-Weighted	Citation-Weighted	Citation-Weighted	Coinventor-Weighted	Coinventor-Weighted	Coinventor-Weighted	Coinventor-Weighted
Prices (log, t-1)	0.243^{***}	0.244^{***}	0.258^{***}	0.260^{***}	0.207^{***}	0.198^{***}	0.259^{***}	0.260^{***}	0.236^{***}	0.238^{***}	0.233^{***}	0.236^{***}
	(0.027)	(0.028)	(0.025)	(0.025)	(0.045)	(0.046)	(0.037)	(0.038)	(0.029)	(0.030)	(0.027)	(0.027)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	192,111	192,133	192,111	192,133	192,111	192,133	192,111	192,133	192,111	192,133	192,111	192,133
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,443,598	1,443,700	1,443,598	1,443,700	1,443,598	1,443,700	1,443,598	1,443,700	1,443,598	1,443,700	1,443,598	1,443,700
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.35: Electricity Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Simple Count	Simple Count	Simple Count	Simple Count	Citation-Weighted	Citation-Weighted	Citation-Weighted	Citation-Weighted	Coinventor-Weighted	Coinventor-Weighted	Coinventor-Weighted	Coinventor-Weighted
Prices (log, t-1)	0.321^{***}	0.334^{***}	0.369^{***}	0.370^{***}	0.503^{***}	0.513^{***}	0.663^{***}	0.665^{***}	0.353^{***}	0.366^{***}	0.350^{***}	0.350^{***}
	(0.039)	(0.040)	(0.038)	(0.038)	(0.054)	(0.057)	(0.049)	(0.049)	(0.039)	(0.040)	(0.040)	(0.040)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	190,174	190,240	190,174	190,240	190,174	190,240	190,174	190,240	190,174	190,240	190,174	190,240
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,433,212	1,433,457	1,433,212	1,433,457	1,433,212	1,433,457	1,433,212	1,433,457	1,433,212	1,433,457	1,433,212	1,433,457
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.36: Household Prices: Baseline Poisson Estimates for Broader Definition of Clean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Simple Count	Simple Count	Simple Count	Simple Count	Citation-Weighted	Citation-Weighted	Citation-Weighted	Citation-Weighted	Coinventor-Weighted	Coinventor-Weighted	Coinventor-Weighted	Coinventor-Weighted
Prices (log, t-1)	0.173^{***}	0.177^{***}	0.194^{***}	0.196^{***}	0.167^{***}	0.172^{***}	0.199^{***}	0.201^{***}	0.193^{***}	0.198^{***}	0.206^{***}	0.209^{***}
	(0.022)	(0.022)	(0.022)	(0.022)	(0.034)	(0.034)	(0.031)	(0.031)	(0.025)	(0.025)	(0.024)	(0.024)
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X	X	X	X	X	X	X
Tenure FEs	X	X	X	X	X	X	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X	X	X	X	X	X	X
Inventor Clusters (SEs)	192,140	192,155	192,140	192,155	192,140	192,155	192,140	192,155	192,140	192,155	192,140	192,155
Price Panel	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced
Price Weights	-	-	GDP	GDP	-	-	GDP	GDP	-	-	GDP	GDP
Observations	1,443,804	1,443,861	1,443,804	1,443,861	1,443,804	1,443,861	1,443,804	1,443,861	1,443,804	1,443,861	1,443,804	1,443,861
Pseudo-R2	0.341	0.341	0.341	0.341	0.397	0.397	0.397	0.397	0.286	0.286	0.286	0.286

Dependent variable: Number of Renewable/Nuclear/Enabling docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.6 Robustness Check: Dropping Multi-Firm Inventors

Table G.37: Dropping Multi-Firm Inventors - One Lag

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.174*	0.179*	0.185	0.176	0.227*	0.193*
	(0.096)	(0.092)	(0.129)	(0.128)	(0.122)	(0.112)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	10,018	10,017	10,018	10,017	10,018	10,017
Observations	44,953	44,929	44,953	44,929	44,953	44,929
Pseudo-R2	0.222	0.224	0.334	0.335	0.230	0.232

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.38: Dropping Multi-Firm Inventors - Distributed Lags

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.475***	0.470***	0.629***	0.629***	0.240	0.255
	(0.139)	(0.141)	(0.206)	(0.210)	(0.166)	(0.164)
Prices (log, t-2)	-0.112	-0.119	-0.044	-0.044	0.334*	0.330*
	(0.146)	(0.146)	(0.213)	(0.211)	(0.187)	(0.186)
Prices (log, t-3)	-0.102	-0.123	-0.054	-0.076	-0.123	-0.186
	(0.146)	(0.133)	(0.189)	(0.177)	(0.180)	(0.157)
Cumulative Effect	0.261	0.228	0.530***	0.509**	0.451**	0.399**
	(0.164)	(0.150)	(0.206)	(0.199)	(0.204)	(0.175)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	5,160	5,160	5,160	5,160	5,160	5,160
Observations	23,605	23,587	23,605	23,587	23,605	23,587
Pseudo-R2	0.220	0.223	0.324	0.326	0.230	0.233

Dependent variable: Number of Renewable/Nuclear docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.7 Additional Results: Effect on Grey, Dirty, and Non-Energy Patenting

In this section, we look at the effect of changes in natural gas prices on other types of patenting, mainly: grey, dirty, and non-energy. The regression tables below replicate the specifications shown in Panels a and b of Table 1 but with different outcome variables. The data sample used in these regressions is also the same as in Table 1, meaning it focuses on clean incumbents. Since only a few clean incumbents also patent in grey and dirty, the number of observations in regressions using grey or dirty patenting as outcome variables is smaller.

We find that increases in natural gas prices lead to a higher number of grey and dirty patents. One caveat here is that this effect concerns only the sample of inventors patenting both in clean and grey or dirty. We interpret this effect as increased incentives to innovate in efficient natural gas technologies or other fossil fuel technologies, such as coal, that could replace natural gas for electricity generation.

We also find that increases in natural gas prices lead to a lower number of non-energy patents. This indicates that the induced innovation effect in energy technologies might come at the expense of innovation in other sectors.

G.7.1 Effect on Grey Patenting

Table G.39: Baseline Poisson Estimates for Grey Patenting (Baseline Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.375***	0.352***	0.574***	0.506***	0.353***	0.350***
	(0.085)	(0.091)	(0.094)	(0.096)	(0.111)	(0.116)
GDP per capita (log, t-1)	6.659***	6.804***	7.277***	7.404***	5.073***	5.182***
	(0.950)	(0.970)	(0.745)	(0.754)	(1.144)	(1.161)
Energy RD&D (log, t-1)	0.064	0.052	0.212**	0.194**	0.106	0.100
	(0.073)	(0.076)	(0.086)	(0.091)	(0.085)	(0.087)
Low-Carbon RD&D (log, t-1)	-0.117	-0.052	-0.323***	-0.174*	-0.147	-0.109
	(0.096)	(0.093)	(0.099)	(0.100)	(0.103)	(0.099)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	18,989	18,989	18,989	18,989	18,989	18,989
Observations	177,049	177,044	177,049	177,044	177,049	177,044
Pseudo-R2	0.233	0.234	0.296	0.297	0.213	0.213

Dependent variable: Number of grey docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.40: Baseline Poisson Estimates for Grey Patenting (Broader Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.096	0.136*	0.176**	0.204**	0.128	0.169*
	(0.070)	(0.077)	(0.077)	(0.080)	(0.088)	(0.096)
GDP per capita (log, t-1)	6.000***	5.459***	6.051***	5.869***	5.185***	4.703***
	(0.699)	(0.770)	(0.586)	(0.621)	(0.837)	(0.916)
Energy RD&D (log, t-1)	0.210***	0.198**	0.356***	0.358***	0.210***	0.195***
	(0.081)	(0.079)	(0.101)	(0.101)	(0.077)	(0.075)
Low-Carbon RD&D (log, t-1)	-0.089	-0.124	-0.354***	-0.346***	-0.090	-0.128
	(0.088)	(0.087)	(0.104)	(0.102)	(0.085)	(0.084)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	26,641	26,641	26,641	26,641	26,641	26,641
Observations	276,159	276,151	276,159	276,151	276,159	276,151
Pseudo-R2	0.217	0.218	0.268	0.269	0.201	0.202

Dependent variable: Number of grey docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.41: Distributed Lag Estimates for Grey Patenting (Baseline Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	-0.197*	-0.187*	-0.008	0.017	-0.316***	-0.300**
	(0.104)	(0.106)	(0.125)	(0.126)	(0.121)	(0.123)
Prices (log, t-2)	0.207**	0.176*	0.032	-0.023	0.425***	0.400***
	(0.104)	(0.104)	(0.138)	(0.138)	(0.123)	(0.121)
Prices (log, t-3)	0.422***	0.406***	0.712***	0.666***	0.322***	0.313***
	(0.103)	(0.104)	(0.136)	(0.135)	(0.117)	(0.118)
L.GDP per capita (log, k$)	8.002***	8.307***	6.869***	7.129***	7.757***	8.084***
	(1.988)	(1.909)	(1.781)	(1.705)	(1.969)	(1.873)
L2.GDP per capita (log, k$)	-1.077	-0.804	-1.082	-0.768	-2.075**	-1.721*
	(0.918)	(0.900)	(1.070)	(1.045)	(0.994)	(0.958)
L3.GDP per capita (log, k$)	-0.714	-0.668	1.594*	1.536*	-1.046	-1.007
	(0.957)	(0.907)	(0.854)	(0.834)	(0.980)	(0.927)
L.Energy RD&D (log, m$)	-0.006	0.001	0.208	0.236*	0.056	0.064
	(0.114)	(0.115)	(0.128)	(0.131)	(0.117)	(0.124)
L2.Energy RD&D (log, m$)	-0.193*	-0.190*	-0.046	-0.033	-0.035	-0.038
	(0.109)	(0.111)	(0.111)	(0.114)	(0.104)	(0.109)
L3.Energy RD&D (log, m$)	-0.081	-0.077	0.034	0.035	-0.081	-0.078
	(0.069)	(0.069)	(0.092)	(0.093)	(0.080)	(0.082)
L.Low-Carbon RD&D (log, m$)	0.008	0.086	-0.232	-0.121	-0.127	-0.074
	(0.128)	(0.130)	(0.141)	(0.146)	(0.123)	(0.129)
L2.Low-Carbon RD&D (log, m$)	0.183	0.206*	0.047	0.089	0.167	0.184
	(0.117)	(0.119)	(0.117)	(0.117)	(0.126)	(0.130)
L3.Low-Carbon RD&D (log, m$)	-0.004	0.006	-0.190*	-0.166*	0.007	0.012
	(0.076)	(0.076)	(0.097)	(0.099)	(0.089)	(0.091)
Cumulative Effect	0.432***	0.395***	0.736***	0.660***	0.431***	0.413***
	(0.099)	(0.106)	(0.123)	(0.124)	(0.114)	(0.121)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	16,293	16,293	16,293	16,293	16,293	16,293
Observations	146,060	146,056	146,060	146,056	146,060	146,056
Pseudo-R2	0.235	0.236	0.297	0.299	0.213	0.214

Dependent variable: Number of grey docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.42: Distributed Lag Estimates for Grey Patenting (Broader Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	-0.197*	-0.187*	-0.008	0.017	-0.316***	-0.300**
	(0.104)	(0.106)	(0.125)	(0.126)	(0.121)	(0.123)
Prices (log, t-2)	0.207**	0.176*	0.032	-0.023	0.425***	0.400***
	(0.104)	(0.104)	(0.138)	(0.138)	(0.123)	(0.121)
Prices (log, t-3)	0.422***	0.406***	0.712***	0.666***	0.322***	0.313***
	(0.103)	(0.104)	(0.136)	(0.135)	(0.117)	(0.118)
L.GDP per capita (log, k$)	8.002***	8.307***	6.869***	7.129***	7.757***	8.084***
	(1.988)	(1.909)	(1.781)	(1.705)	(1.969)	(1.873)
L2.GDP per capita (log, k$)	-1.077	-0.804	-1.082	-0.768	-2.075**	-1.721*
	(0.918)	(0.900)	(1.070)	(1.045)	(0.994)	(0.958)
L3.GDP per capita (log, k$)	-0.714	-0.668	1.594*	1.536*	-1.046	-1.007
	(0.957)	(0.907)	(0.854)	(0.834)	(0.980)	(0.927)
L.Energy RD&D (log, m$)	-0.006	0.001	0.208	0.236*	0.056	0.064
	(0.114)	(0.115)	(0.128)	(0.131)	(0.117)	(0.124)
L2.Energy RD&D (log, m$)	-0.193*	-0.190*	-0.046	-0.033	-0.035	-0.038
	(0.109)	(0.111)	(0.111)	(0.114)	(0.104)	(0.109)
L3.Energy RD&D (log, m$)	-0.081	-0.077	0.034	0.035	-0.081	-0.078
	(0.069)	(0.069)	(0.092)	(0.093)	(0.080)	(0.082)
L.Low-Carbon RD&D (log, m$)	0.008	0.086	-0.232	-0.121	-0.127	-0.074
	(0.128)	(0.130)	(0.141)	(0.146)	(0.123)	(0.129)
L2.Low-Carbon RD&D (log, m$)	0.183	0.206*	0.047	0.089	0.167	0.184
	(0.117)	(0.119)	(0.117)	(0.117)	(0.126)	(0.130)
L3.Low-Carbon RD&D (log, m$)	-0.004	0.006	-0.190*	-0.166*	0.007	0.012
	(0.076)	(0.076)	(0.097)	(0.099)	(0.089)	(0.091)
Cumulative Effect	0.432***	0.395***	0.736***	0.660***	0.431***	0.413***
	(0.099)	(0.106)	(0.123)	(0.124)	(0.114)	(0.121)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	16,293	16,293	16,293	16,293	16,293	16,293
Observations	146,060	146,056	146,060	146,056	146,060	146,056
Pseudo-R2	0.235	0.236	0.297	0.299	0.213	0.214

Dependent variable: Number of grey docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.7.2 Effect on Dirty Patenting

Table G.43: Baseline Poisson Estimates for Dirty Patenting (Baseline Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.307***	0.386***	0.332***	0.382***	0.239***	0.315***
	(0.073)	(0.075)	(0.093)	(0.092)	(0.083)	(0.087)
GDP per capita (log, t-1)	2.071***	1.105**	2.757***	2.003***	1.484***	0.490
	(0.448)	(0.487)	(0.505)	(0.548)	(0.466)	(0.504)
Energy RD&D (log, t-1)	-0.081	-0.081	-0.034	-0.031	-0.126	-0.129*
	(0.067)	(0.065)	(0.082)	(0.079)	(0.077)	(0.075)
Low-Carbon RD&D (log, t-1)	0.230***	0.173**	0.167*	0.112	0.207***	0.151**
	(0.074)	(0.072)	(0.086)	(0.084)	(0.079)	(0.077)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	18,636	18,636	18,636	18,636	18,636	18,636
Observations	197,466	197,458	197,466	197,458	197,466	197,458
Pseudo-R2	0.251	0.251	0.306	0.307	0.230	0.231

Dependent variable: Number of dirty docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.44: Baseline Poisson Estimates for Dirty Patenting (Broad Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.111*	0.201***	0.090	0.143*	0.129*	0.225***
	(0.059)	(0.060)	(0.074)	(0.074)	(0.069)	(0.070)
GDP per capita (log, t-1)	2.548***	1.409***	3.125***	2.416***	1.932***	0.735*
	(0.366)	(0.400)	(0.422)	(0.469)	(0.373)	(0.411)
Energy RD&D (log, t-1)	-0.085*	-0.105**	-0.087	-0.102	-0.116*	-0.134**
	(0.051)	(0.050)	(0.064)	(0.062)	(0.060)	(0.058)
Low-Carbon RD&D (log, t-1)	0.284***	0.219***	0.234***	0.171**	0.284***	0.220***
	(0.057)	(0.056)	(0.069)	(0.067)	(0.064)	(0.063)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	29,491	29,491	29,491	29,491	29,491	29,491
Observations	329,052	329,044	329,052	329,044	329,052	329,044
Pseudo-R2	0.235	0.236	0.276	0.276	0.223	0.224

Dependent variable: Number of dirty docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.45: Distributed Lag Estimates for Dirty Patenting (Baseline Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	-0.009	-0.033	0.123	0.081	-0.084	-0.107
	(0.103)	(0.104)	(0.121)	(0.121)	(0.114)	(0.115)
Prices (log, t-2)	0.093	0.153	0.087	0.133	0.114	0.171
	(0.097)	(0.097)	(0.131)	(0.130)	(0.114)	(0.115)
Prices (log, t-3)	0.343***	0.416***	0.211*	0.284**	0.371***	0.443***
	(0.088)	(0.091)	(0.116)	(0.119)	(0.098)	(0.099)
L.GDP per capita (log, k$)	2.531***	1.993**	2.962***	2.469**	2.352**	1.771
	(0.874)	(0.907)	(1.087)	(1.119)	(1.154)	(1.190)
L2.GDP per capita (log, k$)	-0.981	-1.461	-0.244	-0.627	-0.241	-0.734
	(0.887)	(0.920)	(1.070)	(1.108)	(1.062)	(1.112)
L3.GDP per capita (log, k$)	-0.491	-0.438	0.140	0.129	-1.276	-1.271
	(0.705)	(0.712)	(0.764)	(0.780)	(0.795)	(0.799)
L.Energy RD&D (log, m$)	-0.141	-0.182*	-0.129	-0.169	-0.244**	-0.283***
	(0.096)	(0.097)	(0.121)	(0.121)	(0.108)	(0.109)
L2.Energy RD&D (log, m$)	-0.049	-0.095	0.154	0.099	0.063	0.014
	(0.084)	(0.085)	(0.102)	(0.102)	(0.088)	(0.089)
L3.Energy RD&D (log, m$)	-0.035	-0.057	0.052	0.021	0.056	0.034
	(0.066)	(0.067)	(0.086)	(0.086)	(0.072)	(0.074)
L.Low-Carbon RD&D (log, m$)	0.256**	0.198*	0.137	0.096	0.223*	0.178
	(0.115)	(0.115)	(0.141)	(0.142)	(0.122)	(0.121)
L2.Low-Carbon RD&D (log, m$)	0.163**	0.159**	-0.104	-0.101	0.054	0.053
	(0.081)	(0.081)	(0.113)	(0.111)	(0.087)	(0.087)
L3.Low-Carbon RD&D (log, m$)	0.106	0.088	0.066	0.062	0.123	0.103
	(0.070)	(0.071)	(0.084)	(0.085)	(0.081)	(0.083)
Cumulative Effect	0.427***	0.535***	0.422***	0.498***	0.402***	0.507***
	(0.095)	(0.097)	(0.126)	(0.126)	(0.109)	(0.114)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	16,758	16,758	16,758	16,758	16,758	16,758
Observations	166,201	166,194	166,201	166,194	166,201	166,194
Pseudo-R2	0.248	0.249	0.307	0.308	0.228	0.229

Dependent variable: Number of dirty docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.46: Distributed Lag Estimates for Dirty Patenting (Broad Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	-0.131	-0.163*	-0.086	-0.133	-0.104	-0.126
	(0.085)	(0.086)	(0.101)	(0.102)	(0.095)	(0.097)
Prices (log, t-2)	0.079	0.134*	0.188*	0.228**	0.041	0.100
	(0.078)	(0.079)	(0.104)	(0.104)	(0.092)	(0.093)
Prices (log, t-3)	0.244***	0.318***	0.043	0.114	0.316***	0.388***
	(0.070)	(0.072)	(0.089)	(0.091)	(0.081)	(0.082)
L.GDP per capita (log, k$)	3.445***	2.965***	4.292***	4.008***	3.164***	2.707***
	(0.699)	(0.718)	(0.892)	(0.912)	(0.916)	(0.937)
L2.GDP per capita (log, k$)	-0.405	-0.821	0.766	0.453	-0.263	-0.752
	(0.723)	(0.751)	(0.898)	(0.932)	(0.873)	(0.915)
L3.GDP per capita (log, k$)	-1.315**	-1.341**	-1.428**	-1.598**	-1.778**	-1.827**
	(0.629)	(0.638)	(0.694)	(0.711)	(0.726)	(0.737)
L.Energy RD&D (log, m$)	-0.186**	-0.248***	-0.203**	-0.258**	-0.243***	-0.300***
	(0.076)	(0.077)	(0.101)	(0.100)	(0.090)	(0.090)
L2.Energy RD&D (log, m$)	-0.023	-0.077	0.132	0.074	0.054	0.000
	(0.067)	(0.068)	(0.082)	(0.081)	(0.072)	(0.073)
L3.Energy RD&D (log, m$)	-0.052	-0.079	0.050	0.014	-0.019	-0.045
	(0.052)	(0.052)	(0.067)	(0.066)	(0.060)	(0.061)
L.Low-Carbon RD&D (log, m$)	0.283***	0.223**	0.136	0.104	0.293***	0.240**
	(0.090)	(0.089)	(0.113)	(0.114)	(0.102)	(0.101)
L2.Low-Carbon RD&D (log, m$)	0.156**	0.146**	-0.031	-0.026	0.088	0.082
	(0.065)	(0.065)	(0.091)	(0.090)	(0.075)	(0.075)
L3.Low-Carbon RD&D (log, m$)	0.153***	0.138**	0.099	0.099	0.201***	0.187***
	(0.055)	(0.056)	(0.067)	(0.068)	(0.067)	(0.067)
Cumulative Effect	0.192**	0.290***	0.146	0.209**	0.254***	0.362***
	(0.076)	(0.078)	(0.097)	(0.098)	(0.089)	(0.091)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	26,234	26,234	26,234	26,234	26,234	26,234
Observations	272,701	272,694	272,701	272,694	272,701	272,694
Pseudo-R2	0.233	0.234	0.276	0.276	0.222	0.223

Dependent variable: Number of dirty docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

G.7.3 Effect on Non-Energy Patenting

Table G.47: Baseline Poisson Estimates for Non-Energy Patenting (Baseline Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	-0.299***	-0.211***	-0.496***	-0.429***	-0.238**	-0.163
	(0.058)	(0.055)	(0.053)	(0.050)	(0.103)	(0.100)
GDP per capita (log, t-1)	6.550***	4.688***	6.202***	5.121***	5.616***	3.835***
	(0.256)	(0.276)	(0.268)	(0.274)	(0.348)	(0.375)
Energy RD&D (log, t-1)	-0.016	-0.058***	-0.056*	-0.078***	0.019	-0.020
	(0.024)	(0.022)	(0.029)	(0.028)	(0.032)	(0.028)
Low-Carbon RD&D (log, t-1)	0.075*	0.011	-0.089**	-0.122***	-0.000	-0.044
	(0.045)	(0.042)	(0.045)	(0.041)	(0.066)	(0.062)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	97,656	97,656	97,656	97,656	97,656	97,656
Observations	767,685	767,685	767,685	767,685	767,685	767,685
Pseudo-R2	0.659	0.661	0.636	0.639	0.600	0.603

Dependent variable: Number of non-energy docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.48: Baseline Poisson Estimates for Non-Energy Patenting (Broader Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	-0.285***	-0.184***	-0.441***	-0.353***	-0.248***	-0.164***
	(0.039)	(0.036)	(0.041)	(0.039)	(0.066)	(0.063)
GDP per capita (log, t-1)	6.914***	5.101***	6.408***	5.228***	5.921***	4.147***
	(0.181)	(0.195)	(0.211)	(0.229)	(0.237)	(0.253)
Energy RD&D (log, t-1)	0.001	-0.035**	-0.048**	-0.066***	0.054**	0.019
	(0.016)	(0.015)	(0.024)	(0.022)	(0.021)	(0.019)
Low-Carbon RD&D (log, t-1)	0.046*	-0.020	-0.059*	-0.114***	-0.024	-0.071*
	(0.028)	(0.027)	(0.031)	(0.028)	(0.041)	(0.039)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	176,219	176,219	176,219	176,219	176,219	176,219
Observations	1,419,338	1,419,338	1,419,338	1,419,338	1,419,338	1,419,338
Pseudo-R2	0.620	0.623	0.650	0.652	0.563	0.566

Dependent variable: Number of non-energy docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.49: Distributed Lag Estimates for Non-Energy Patenting (Baseline Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.435***	0.305***	0.322***	0.217***	0.429***	0.308***
	(0.043)	(0.039)	(0.049)	(0.050)	(0.060)	(0.050)
Prices (log, t-2)	-0.357***	-0.318***	-0.391***	-0.380***	-0.297***	-0.250***
	(0.044)	(0.043)	(0.056)	(0.057)	(0.075)	(0.072)
Prices (log, t-3)	-0.651***	-0.503***	-0.701***	-0.582***	-0.628***	-0.479***
	(0.059)	(0.049)	(0.069)	(0.065)	(0.119)	(0.096)
L.GDP per capita (log, k$)	4.630***	3.962***	3.930***	3.596***	4.634***	3.885***
	(0.450)	(0.452)	(0.517)	(0.517)	(0.566)	(0.551)
L2.GDP per capita (log, k$)	0.910**	0.613	2.403***	2.187***	0.263	-0.050
	(0.459)	(0.462)	(0.465)	(0.482)	(0.750)	(0.751)
L3.GDP per capita (log, k$)	0.744	0.527	0.752*	0.555	1.257	1.036
	(0.556)	(0.562)	(0.450)	(0.458)	(0.974)	(0.980)
L.Energy RD&D (log, m$)	0.271***	0.180***	0.173***	0.130**	0.314***	0.217***
	(0.062)	(0.054)	(0.066)	(0.065)	(0.094)	(0.078)
L2.Energy RD&D (log, m$)	0.121**	0.047	0.103**	0.057	0.181**	0.109*
	(0.047)	(0.041)	(0.051)	(0.049)	(0.070)	(0.057)
L3.Energy RD&D (log, m$)	0.091***	0.054**	0.099***	0.078***	0.098***	0.064***
	(0.024)	(0.022)	(0.028)	(0.027)	(0.029)	(0.024)
L.Low-Carbon RD&D (log, m$)	0.224***	0.211***	0.052	0.081	0.061	0.049
	(0.069)	(0.065)	(0.055)	(0.055)	(0.082)	(0.078)
L2.Low-Carbon RD&D (log, m$)	0.085*	0.081*	-0.014	-0.002	0.025	0.016
	(0.047)	(0.044)	(0.045)	(0.041)	(0.061)	(0.057)
L3.Low-Carbon RD&D (log, m$)	-0.043*	-0.049**	-0.044	-0.046	-0.067**	-0.068**
	(0.026)	(0.024)	(0.045)	(0.048)	(0.028)	(0.027)
Cumulative Effect	-0.574***	-0.515***	-0.771***	-0.744***	-0.496***	-0.421***
	(0.073)	(0.070)	(0.065)	(0.064)	(0.144)	(0.140)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	86,469	86,469	86,469	86,469	86,469	86,469
Observations	660,863	660,863	660,863	660,863	660,863	660,863
Pseudo-R2	0.663	0.664	0.642	0.643	0.601	0.602

Dependent variable: Number of non-energy docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

Table G.50: Distributed Lag Estimates with Non-Energy Patenting (Broader Definition of Clean)

	(1) Simple Count	(2) Simple Count	(3) Citation-Weighted	(4) Citation-Weighted	(5) Coinventor-Weighted	(6) Coinventor-Weighted
Prices (log, t-1)	0.391***	0.279***	0.327***	0.248***	0.386***	0.280***
	(0.038)	(0.033)	(0.069)	(0.067)	(0.057)	(0.047)
Prices (log, t-2)	-0.398***	-0.344***	-0.435***	-0.397***	-0.360***	-0.302***
	(0.033)	(0.031)	(0.055)	(0.054)	(0.055)	(0.051)
Prices (log, t-3)	-0.569***	-0.429***	-0.671***	-0.569***	-0.568***	-0.430***
	(0.043)	(0.034)	(0.063)	(0.061)	(0.084)	(0.064)
L.GDP per capita (log, k$)	4.146***	3.490***	3.061***	2.706***	4.093***	3.369***
	(0.309)	(0.310)	(0.390)	(0.388)	(0.405)	(0.391)
L2.GDP per capita (log, k$)	1.593***	1.275***	2.990***	2.737***	1.083**	0.742
	(0.308)	(0.310)	(0.329)	(0.333)	(0.511)	(0.515)
L3.GDP per capita (log, k$)	0.488	0.300	0.770**	0.525	0.864	0.683
	(0.383)	(0.388)	(0.348)	(0.344)	(0.696)	(0.704)
L.Energy RD&D (log, m$)	0.311***	0.216***	0.258***	0.205***	0.377***	0.273***
	(0.044)	(0.037)	(0.060)	(0.058)	(0.070)	(0.055)
L2.Energy RD&D (log, m$)	0.088***	0.018	0.029	-0.014	0.159***	0.088**
	(0.034)	(0.029)	(0.040)	(0.038)	(0.051)	(0.041)
L3.Energy RD&D (log, m$)	0.067***	0.033**	0.009	-0.012	0.085***	0.052**
	(0.019)	(0.017)	(0.027)	(0.026)	(0.024)	(0.021)
L.Low-Carbon RD&D (log, m$)	0.248***	0.217***	0.064	0.063	0.097	0.068
	(0.051)	(0.047)	(0.042)	(0.041)	(0.069)	(0.064)
L2.Low-Carbon RD&D (log, m$)	0.108***	0.095***	0.096**	0.095**	0.047	0.031
	(0.034)	(0.031)	(0.043)	(0.040)	(0.049)	(0.044)
L3.Low-Carbon RD&D (log, m$)	-0.052***	-0.058***	-0.066**	-0.064*	-0.076***	-0.077***
	(0.019)	(0.018)	(0.034)	(0.035)	(0.024)	(0.022)
Cumulative Effect	-0.576***	-0.494***	-0.779***	-0.719***	-0.542***	-0.452***
	(0.054)	(0.048)	(0.053)	(0.050)	(0.099)	(0.091)
Year FEs	X	X	X	X	X	X
Inventor FEs	X	X	X	X	X	X
Tenure FEs		X		X		X
Country-Year Covariates	X	X	X	X	X	X
Inventor Clusters (SEs)	153,443	153,443	153,443	153,443	153,443	153,443
Observations	1,202,257	1,202,257	1,202,257	1,202,257	1,202,257	1,202,257
Pseudo-R2	0.626	0.627	0.657	0.659	0.565	0.566

Dependent variable: Number of non-energy docdb patent families.

Poisson pseudo-maximum likelihood. Standard errors clustered by inventor in parentheses.

H Robustness of Inventor Entry Results

H.1 Primary Outcomes: Entry by Renewable and Nuclear Inventors

Table H.1: Renewable and Nuclear Inventor Entry Elasticities, Balanced Panel

	(1) New to Patenting	(2) New to Patenting	(3) From Grey/Dirty	(4) From Grey/Dirty	(5) From Non-Energy	(6) From Non-Energy
Prices (log, t-1)	0.212*	0.237	0.143	0.535***	0.122	0.423***
	(0.127)	(0.180)	(0.099)	(0.139)	(0.105)	(0.163)
Prices (log, t-2)		-0.040		-0.351***		-0.251*
		(0.155)		(0.134)		(0.148)
Prices (log, t-3)		0.311		0.469***		0.031
		(0.210)		(0.124)		(0.158)
Cumulative Effect		0.509***		0.653***		0.203
		(0.168)		(0.122)		(0.160)
Year FEs	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X
Firm Clusters (SEs)	3,822	3,680	4,970	4,777	4,930	4,708
Observations	52,982	43,262	68,709	55,612	68,223	55,075
Pseudo-R2	0.671	0.680	0.591	0.595	0.624	0.631

Dependent variables: number of renewable/nuclear inventors per group.
Sample: balanced panel from 2000 to 2014.
Poisson pseudo-maximum likelihood. Standard errors clustered by firm in parentheses.

Table H.2: Renewable and Nuclear Inventor Entry Elasticities, Unbalanced Panel

	(1) New to Patenting	(2) New to Patenting	(3) From Grey/Dirty	(4) From Grey/Dirty	(5) From Non-Energy	(6) From Non-Energy
Prices (log, t-1)	0.242**	0.228	0.070	0.509***	0.106	0.356**
	(0.118)	(0.170)	(0.097)	(0.132)	(0.095)	(0.155)
Prices (log, t-2)		0.079		-0.415***		-0.257*
		(0.147)		(0.130)		(0.144)
Prices (log, t-3)		0.182		0.410***		0.078
		(0.197)		(0.119)		(0.151)
Cumulative Effect		0.490***		0.504***		0.177
		(0.158)		(0.115)		(0.146)
Year FEs	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X
Firm Clusters (SEs)	8,422	6,915	9,461	8,320	9,628	8,215
Observations	87,377	65,258	105,833	80,858	106,254	80,329
Pseudo-R2	0.613	0.638	0.544	0.555	0.566	0.583

Dependent variables: number of renewable/nuclear inventors per group.
Sample: unbalanced panel from 2000 to 2014.
Poisson pseudo-maximum likelihood. Standard errors clustered by firm in parentheses.

H.2 Alternative Outcomes: Broader Definition of Clean

Table H.3: Clean Inventor Entry Elasticities, Balanced Panel

	(1) New to Patenting	(2) New to Patenting	(3) From Grey/Dirty	(4) From Grey/Dirty	(5) From Non-Energy	(6) From Non-Energy
Prices (log, t-1)	0.157	0.367***	0.046	0.443***	-0.039	0.441***
	(0.101)	(0.132)	(0.092)	(0.129)	(0.084)	(0.126)
Prices (log, t-2)		-0.023		-0.056		-0.255**
		(0.138)		(0.131)		(0.115)
Prices (log, t-3)		0.153		0.216*		-0.059
		(0.171)		(0.119)		(0.118)
Cumulative Effect		0.497***		0.603***		0.126
		(0.132)		(0.103)		(0.117)
Year FEs	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X
Firm Clusters (SEs)	5,779	5,532	4,958	4,722	6,720	6,422
Observations	80,145	65,030	68,583	55,069	93,089	75,181
Pseudo-R2	0.728	0.740	0.566	0.567	0.688	0.696

Dependent variables: number of clean inventors per group.
Sample: balanced panel from 2000 to 2014.
Poisson pseudo-maximum likelihood. Standard errors clustered by firm in parentheses.

Table H.4: Clean Inventor Entry Elasticities, Unbalanced Panel

	(1) New to Patenting	(2) New to Patenting	(3) From Grey/Dirty	(4) From Grey/Dirty	(5) From Non-Energy	(6) From Non-Energy
Prices (log, t-1)	0.153	0.343***	-0.060	0.358***	-0.051	0.399***
	(0.096)	(0.123)	(0.090)	(0.125)	(0.078)	(0.121)
Prices (log, t-2)		0.054		-0.082		-0.267**
		(0.130)		(0.127)		(0.111)
Prices (log, t-3)		0.037		0.146		-0.041
		(0.162)		(0.115)		(0.113)
Cumulative Effect		0.434***		0.422***		0.092
		(0.125)		(0.101)		(0.108)
Year FEs	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X
Country-Year Covariates	X	X	X	X	X	X
Firm Clusters (SEs)	13,190	10,773	9,474	8,248	14,052	11,836
Observations	135,662	100,377	105,814	80,034	151,739	113,549
Pseudo-R2	0.670	0.695	0.516	0.525	0.633	0.651

Dependent variables: number of clean inventors per group.
Sample: unbalanced panel from 2000 to 2014.
Poisson pseudo-maximum likelihood. Standard errors clustered by firm in parentheses.

I Carbon Pricing Details and Robustness

I.1 Implementation

Our empirical strategy allows us to estimate elasticities that characterize how natural gas price variation induces innovation through the intensive margin by increasing the rate at which incumbent inventors patent, and through the extensive margin by increasing the number of inventors that work on clean technology. This section details the back-of-the-envelope calculation we use to combine the effects along those two margins and to analyze the potential impacts of a broad-based policy to price carbon.

The total number of clean patent families in a given year can be written as the product of the average number of patents filed per year by an inventor and the number of active inventors:

$$PAT_t^C = \overline{PAT}_t^C N_t. \tag{I.1}$$

To study the role of entry by inventors of different types, we decompose the number of incumbent inventors based on its evolution over time:

$$N_t = N_{t-1} + E_t^{g/d} + E_t^{non-energy} + E_t^{new} - X_t \tag{I.2}$$

where E_t^k denotes the number of inventors of type k who enter at the beginning of period t, and X_t denotes the number of incumbent inventors who exit at the beginning of period t.[7]

Taking the derivative of both sides of equation I.1 with respect to lagged natural gas prices and substituting equation I.2 yields

$$\frac{dPAT_t^C}{dP_{t-1}} = \frac{d\overline{PAT}_t^C}{dP_{t-1}} N_t + \overline{PAT}_t^C \frac{dN_t}{dP_{t-1}} \tag{I.3}$$

$$= \frac{d\overline{PAT}_t^C}{dP_{t-1}} N_t + \overline{PAT}_t^C \left(\frac{dN_{t-1}}{dP_{t-1}} + \frac{dE_t^{g/d}}{dP_{t-1}} + \frac{dE_t^{non-energy}}{dP_{t-1}} + \frac{dE_t^{new}}{dP_{t-1}} - \frac{dX_t}{dP_{t-1}} \right) \tag{I.4}$$

The first term captures the intensive margin change in patenting from a change in natural gas prices, holding the number of incumbent inventors fixed.

The second term captures the extensive margin change in patenting from a change in the number of inventors of each type, holding expected patenting per entrant fixed. This term is comprised of several parts. For clarity, the measure of average patenting output, $\overline{PAT}_t^C$, is unconditional and does not depend directly on the type of inventor (we relax this below). Within the parentheses, the first derivative is assumed to be zero based on timing: individuals enter and exit at the beginning of the year based on prices in the prior year, before prices for the coming year are realized, so there is no contemporaneous effect of prices on the number of incumbents. We use firm-level data to

7. Entrants are classified into types based on their prior patenting activity. g/d denotes inventors who have previously patented in grey and/or dirty technology but not in clean technology. $non-energy$ denotes inventors who have previously patented in technology areas outside of the set of energy technologies studied in this paper. *new* denotes inventors who were not previously observed in the patent data.

estimate the effects of natural gas prices on entry by inventors of each type, as described in Section 3.3. Since we do not directly observe exit, we assume that the rate of exit is not affected by natural gas prices. If higher natural gas prices led to lower rates of exit, this analysis would understate the role of extensive margin responses (and vice versa).

We approximate the aggregate impact of a change in natural gas prices by rewriting equation I.4 in terms of elasticities and multiplying both sides by the percentage change in prices, $\Delta P_t(\%)$:

$$\Delta PAT_t^C = \varepsilon_P^{\overline{PAT}^C} \overline{PAT}_t^C N_t \Delta P_t(\%) + \sum_k \overline{PAT}_t^{C,k} E_t^k \varepsilon_P^{E^k} \Delta P_t(\%), \tag{I.5}$$

where $\varepsilon_P^{\overline{PAT}_t^C}$ is the elasticity of output with respect to natural gas prices, and $\varepsilon_P^{E^k}$ is the elasticity of the number of entrants of type k with respect to natural gas prices. To provide a richer characterization of the mechanisms of induced innovation, we allow for average patenting rates to vary by entrant type, as denoted by the k subscript in $\overline{PAT}_t^{C,k}$. To compute effects of a persistent price change over a time horizon longer than one year, we further allow for average patenting by new entrants to vary over the course of their tenure. We also account for how a persistent price change has persistent effects on entry.

We use this framework to quantify the potential effects of carbon pricing on the amount and sources of clean innovation. To do so, we first compute how pricing carbon would increase the price of natural gas. For the social cost of carbon, we use the current U.S. Government value of \$51 per metric ton of CO_2 (in 2020 terms). We deflate this value to base year dollars using the U.S. GDP implicit price deflator from OECD (2023). We then convert the social cost of carbon into the same units as the natural gas price data (dollars per megawatt-hour) using conversion factors of 2,204.6 pounds per metric ton,[8] 0.97 pounds CO_2 per kilowatt-hour for electricity generation from natural gas,[9] and 1,000 kilowatt-hours per megawatt-hour. After deflation and conversion, the U.S. Government value of the social cost of carbon corresponds to 54% of the GDP-weighted global average price of natural gas in 2014.

Focusing on 2014 as our base year, we compute the predicted number of additional clean patents that would be generated over the course of 10 years in response to a permanent increase in the natural gas price equivalent to the social cost of carbon. Table 3 in the main text presents the resulting predictions in aggregate and by margin of response. Tables I.1 and I.3 in this appendix present analogous results from different model specifications and outcome variables to assess the robustness of the results.[10]

Inference. We compute standard errors via the delta method. To simplify notation, equation I.5 can be rewritten as

8. Source: EPA's Greenhouse Gases Equivalencies Calculator - Calculations and References, https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references, accessed May 10, 2023.

9. Source: U.S. Energy Information Administration State Electricity Profiles Tables 5 and 7, with data from 2021, https://www.eia.gov/tools/faqs/faq.php?id=74&t=11, accessed May 10, 2023.

10. For the appendix results that use distributed lag models, we use the cumulative effect estimates and treat them as if they take effect immediately rather than phasing in over three years for simplicity. This approach is conservative insofar as accounting for the gradual phase in of the effects would shrink the contribution of the extensive margin relative to the intensive margin, which is the main focus of our analysis. This is because the intensive margin effects phase in quickly (Table G.3), whereas the extensive margin effects phase in more slowly (Table H.1).

$$\Delta PAT_t^C = c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}$$

where all the non-stochastic terms are subsumed into a type-specific constant, c^k, with c^{inc} denoting the constant for incumbents.

Using this notation, the level of the change in patents attributable to incumbents is $c^{inc}\varepsilon_P^{\overline{PAT}^C}$ and the derivative of the level with respect to the output elasticity is c^{inc}. Applying the delta method, we approximate the standard error of the change in patenting attributable to incumbents as the product of the standard error of the output elasticity and c^{inc}. Standard errors for the other level changes are computed analogously using their respective elasticities' standard errors and type-specific constants.

The share of the change in patents attributable to incumbents can be written as:

$$s^{inc}(\varepsilon) = \left(c^{inc}\varepsilon_P^{\overline{PAT}^C}\right)\left(c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}\right)^{-1}.$$

By the delta method, the variance of the share is approximately

$$Var\left(s^{inc}(\varepsilon)\right) \approx \nabla s^{inc}(\varepsilon)^T \frac{\Sigma}{n} \nabla s^{inc}(\varepsilon)$$

where the gradient of the share with respect to the elasticities is

$$\nabla s^{inc}(\varepsilon) = \begin{bmatrix} c^{inc}\left(c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}\right)^{-1} - c^{inc}\left(c^{inc}\varepsilon_P^{\overline{PAT}^C}\right)\left(c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}\right)^{-2} \\ -c^{g/d}\left(c^{inc}\varepsilon_P^{\overline{PAT}^C}\right)\left(c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}\right)^{-2} \\ -c^{non-energy}\left(c^{inc}\varepsilon_P^{\overline{PAT}^C}\right)\left(c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}\right)^{-2} \\ -c^{new}\left(c^{inc}\varepsilon_P^{\overline{PAT}^C}\right)\left(c^{inc}\varepsilon_P^{\overline{PAT}^C} + \sum_k c^k \varepsilon_P^{E^k}\right)^{-2} \end{bmatrix}.$$

Since the elasticities are estimated separately using different data, their covariances are unknown, so we assume they are independent and use the individual variance estimates to construct the variance-covariance matrix Σ. Standard errors for the other shares are computed analogously using their respective gradients.

I.2 Limitations

First, this analysis is an approximation. While the price change we study is on the same order of magnitude as the country-level natural gas price variation observed in the raw data, our first-order approximation does not account for higher-order effects of natural gas prices on innovation by incumbents and entry by new inventors. If the supply of patents or inventors are highly convex, our predictions may overstate the magnitude of induced innovation.

Second, our analysis focuses on the effects of a change in natural gas prices. In reality, carbon pricing would also increase the price of other emitting sources of electricity generation such as coal. Furthermore, economy-wide carbon pricing could lead to increased demand for electricity from other sectors, such as electric vehicle charging from the transportation sector, which would also affect the returns to clean innovation. Both of these effects are beyond the scope of our analysis.

Third, our analysis does not account for differences in the quality of different patents. The results in Tables 3 and I.1 through I.3 are simple counts of patent families. Given the relative magnitudes of the estimates in Table 1, the effects are likely to be larger for alternative measures such as citation-weighted patents that attempt to proxy for the quality of innovations.

I.3 Robustness of Carbon Pricing Simulation Results

I.3.1 Alternative Specifications

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	32,169	81.4
	(4,241)	(6.8)
Extensive margin response		
Entry from grey/dirty	1,285	3.3
	(894)	(2.2)
Entry from non-energy	1,381	3.5
	(1,188)	(2.9)
Entry to patenting	4,672	11.8
	(2,797)	(6.4)
Total	39,508	100.0
	(5,293)	.

(a) Single lag, balanced firm panel

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	37,886	66.1
	(5,326)	(5.8)
Extensive margin response		
Entry from grey/dirty	5,884	10.3
	(1,099)	(2.1)
Entry from non-energy	2,299	4.0
	(1,812)	(3.1)
Entry to patenting	11,237	19.6
	(3,709)	(5.6)
Total	57,307	100.0
	(6,828)	.

(b) Distributed lag, balanced firm panel

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	32,169	76.6
	(4,241)	(7.8)
Extensive margin response		
Entry from grey/dirty	865	2.1
	(1,198)	(2.8)
Entry from non-energy	1,501	3.6
	(1,346)	(3.1)
Entry to patenting	7,467	17.8
	(3,637)	(7.4)
Total	42,004	100.0
	(5,870)	.

(c) Single lag, unbalanced firm panel

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	37,886	61.4
	(5,326)	(6.4)
Extensive margin response		
Entry from grey/dirty	6,224	10.1
	(1,420)	(2.4)
Entry from non-energy	2,498	4.0
	(2,060)	(3.2)
Entry to patenting	15,094	24.5
	(4,867)	(6.4)
Total	61,702	100.0
	(7,637)	.

(d) Distributed lag, unbalanced firm panel

Table I.1: Predicted Impacts of Carbon Pricing for Narrow Definition of Clean

Note: Predicted changes in the number of renewable and nuclear patent families due to a persistent 54% increase in natural gas prices over the course of 10 years, relative to a base year of 2014. Each panel uses elasticities and other inputs based on a different lag structure and firm dataset. Both the balanced and unbalanced firm panels range from 2000 to 2014. Standard errors are constructed using the delta method. Panel a reproduces the results from Table 3 in the main text. The total change in patenting in Panel a represents an increase of 36% relative to baseline patenting rates.

I.3.2 Alternative Base Year: 2010

The qualitative findings are robust to using alternative base years other than 2014. Table I.2 presents results using 2010 as the base year. Both the level of induced patenting and the share of induced patenting attributable to incumbent inventors are higher than in Table I.1.

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	44,484	83.3
	(5,864)	(6.1)
Extensive margin response		
Entry from grey/dirty	1,823	3.4
	(1,267)	(2.3)
Entry from non-energy	2,620	4.9
	(2,254)	(4.1)
Entry to patenting	4,458	8.4
	(2,669)	(4.7)
Total	53,385	100.0
	(6,942)	.

(a) Single lag, balanced firm panel

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	52,389	69.1
	(7,365)	(5.6)
Extensive margin response		
Entry from grey/dirty	8,346	11.0
	(1,559)	(2.2)
Entry from non-energy	4,361	5.8
	(3,438)	(4.3)
Entry to patenting	10,723	14.1
	(3,539)	(4.3)
Total	75,819	100.0
	(9,001)	.

(b) Distributed lag, balanced firm panel

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	44,484	78.3
	(5,864)	(7.3)
Extensive margin response		
Entry from grey/dirty	1,180	2.1
	(1,632)	(2.8)
Entry from non-energy	2,991	5.3
	(2,681)	(4.5)
Entry to patenting	8,174	14.4
	(3,981)	(6.2)
Total	56,828	100.0
	(7,752)	.

(c) Single lag, unbalanced firm panel

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	52,389	63.6
	(7,365)	(6.3)
Extensive margin response		
Entry from grey/dirty	8,484	10.3
	(1,936)	(2.4)
Entry from non-energy	4,975	6.0
	(4,104)	(4.7)
Entry to patenting	16,522	20.1
	(5,328)	(5.6)
Total	82,370	100.0
	(10,160)	.

(d) Distributed lag, unbalanced firm panel

Table I.2: Predicted Impacts of Carbon Pricing for Narrow Definition of Clean

Note: Predicted changes in the number of renewable and nuclear patent families due to a persistent 58% increase in natural gas prices over the course of 10 years, relative to a base year of 2010. Each panel uses elasticities and other inputs based on a different lag structure and firm dataset. Both the balanced and unbalanced firm panels range from 2000 to 2014. Standard errors are constructed using the delta method. The total change in patenting in Panel a represents an increase of 37% relative to baseline patenting rates.

I.3.3 Alternative Outcome: Clean Patenting

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	45,405	87.1
	(5,082)	(9.0)
Extensive margin response		
Entry from grey/dirty	452	0.9
	(900)	(1.7)
Entry from non-energy	-1,061	-2.0
	(2,264)	(4.4)
Entry to patenting	7,351	14.1
	(4,724)	(7.9)
Total	52,146	100.0
	(7,354)	.

(a) Single lag, balanced firm panel

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	63,274	66.0
	(7,073)	(5.4)
Extensive margin response		
Entry from grey/dirty	5,908	6.2
	(1,009)	(1.2)
Entry from non-energy	3,416	3.6
	(3,172)	(3.2)
Entry to patenting	23,270	24.3
	(6,180)	(5.3)
Total	95,868	100.0
	(9,965)	.

(b) Distributed lag, balanced firm panel

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	45,405	86.6
	(5,082)	(10.9)
Extensive margin response		
Entry from grey/dirty	-792	-1.5
	(1,195)	(2.3)
Entry from non-energy	-1,680	-3.2
	(2,569)	(5.1)
Entry to patenting	9,493	18.1
	(5,921)	(9.5)
Total	52,427	100.0
	(8,301)	.

(c) Single lag, unbalanced firm panel

Source	Patents	Share (%)
Intensive margin response		
Incumbent inventors	63,274	64.0
	(7,073)	(6.2)
Extensive margin response		
Entry from grey/dirty	5,592	5.7
	(1,338)	(1.4)
Entry from non-energy	3,036	3.1
	(3,564)	(3.5)
Entry to patenting	26,896	27.2
	(7,747)	(6.1)
Total	98,798	100.0
	(11,159)	.

(d) Distributed lag, unbalanced firm panel

Table I.3: Predicted Impacts of Carbon Pricing for Broad Definition of Clean

Note: Predicted changes in the number of clean patent families due to a persistent 54% increase in natural gas prices over the course of 10 years, relative to a base year of 2014. Each panel uses elasticities and other inputs based on a different lag structure and firm dataset. Both the balanced and unbalanced firm panels range from 2000 to 2014. Standard errors are constructed using the delta method.

J Robustness to Using the Log of Exposure-Weighted Prices

In this section, we present the main results based on constructing prices as the natural logarithm of inventors' exposure-weighted prices, rather than the inventors' exposure-weighted average of the natural logarithm of prices as in the main text. This alternative approach provides an intuitive interpretation of the weighted average of prices as the price that inventors are exposed to.[11] For this appendix, we calculate the price inventor i is exposed to in year t as:

$$\ln P_{it} = \ln\left(\sum_j s_{ij} \sum_c \frac{s_{jc} GDP_c}{\sum_c s_{jc} GDP_c} P_{ct}\right).$$

Tables J.1, J.2, and J.3 summarize the results of using this approach to produce Tables 1, 2, and 3 in the main text. Our results are robust to using this alternative functional form.

11. The paper focuses instead on results that use the exposure-weighted average of the log of prices because that approach follows prior work in this area (e.g., Noailly and Smeets 2015; Aghion et al. 2016) and it is able to rely on results from the methodological literature on shift-share research designs (e.g., Adão et al. 2019; Goldsmith-Pinkham et al. 2020; Borusyak et al. 2022).

Table J.1: Estimates of Incumbent Inventors' Elasticity of Patenting with Respect to Natural Gas Prices

	Count of Clean Patent Families					
	Simple Count		Citation-Weighted		Coinventor-Weighted	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline Poisson estimates						
Prices (log, t-1)	0.589	0.511	0.618	0.535	0.538	0.469
	(0.038)	(0.038)	(0.049)	(0.050)	(0.048)	(0.048)
Inventors	101,823	101,823	101,823	101,823	101,823	101,823
Observations	728,482	728,482	728,482	728,482	728,482	728,482
Pseudo-R2	0.291	0.292	0.373	0.375	0.265	0.266
Panel B: Instrumental variable estimates						
Prices (log, t-1)	0.586	0.391	0.847	0.626	0.471	0.281
	(0.061)	(0.062)	(0.085)	(0.086)	(0.075)	(0.076)
Inventors	101,823	101,823	101,823	101,823	101,823	101,823
Observations	728,482	728,482	728,482	728,482	728,482	728,482
First-stage F-statistic	163	163	163	163	163	163
Panel C: Distributed lag estimates						
Cumulative effect (3 lags)	0.672	0.583	0.622	0.544	0.677	0.578
	(0.052)	(0.053)	(0.070)	(0.071)	(0.060)	(0.062)
Inventors	80,787	80,787	80,787	80,787	80,787	80,787
Observations	572,174	572,174	572,174	572,174	572,174	572,174
Pseudo-R2	0.294	0.295	0.370	0.372	0.267	0.268
Year fixed effects	X	X	X	X	X	X
Inventor fixed effects	X	X	X	X	X	X
Tenure fixed effects		X		X		X
Country-year covariates	X	X	X	X	X	X

Table J.2: Estimates of the Elasticity of Inventor Entry with Respect to Natural Gas Prices

	Number of Clean Inventors		
	New to Patenting (1)	From Grey/Dirty (2)	From Non-Energy (3)
Panel A: Baseline Poisson estimates			
Prices (log, t-1)	0.252	0.312	0.215
	(0.129)	(0.111)	(0.122)
Firms	3,822	4,970	4,930
Observations	52,982	68,709	68,223
Pseudo-R2	0.671	0.592	0.625
Panel B: Distributed lag estimates			
Cumulative effect (3 lags)	0.570	0.639	0.161
	(0.172)	(0.127)	(0.176)
Firms	3,680	4,777	4,708
Observations	43,262	55,612	55,075
Pseudo-R2	0.680	0.595	0.631
Year fixed effects	X	X	X
Firm fixed effects	X	X	X
Country-year covariates	X	X	X

Table J.3: Predicted Impacts of Carbon Pricing on Clean Patenting

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	49,656	71.1
	(5,326)	(5.0)
Extensive margin response		
Entry from grey/dirty	5,758	8.2
	(1,144)	(1.7)
Entry from non-energy	1,824	2.6
	(1,994)	(2.8)
Entry to patenting	12,584	18.0
	(3,797)	(4.7)
Total	69,821	100.0
	(6,933)	.

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