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Induced Innovation, Inventors, and the Energy Transition

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 findings suggest a role for policy to increase the supply of clean inventors to help mitigate climate change.

JEL-Codes: O310, Q550, Q400.

Keywords: inventors, energy technology, induced innovation.

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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-fourth 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, that is, on already-active inventors, and that the entry of new inventors plays a more minor role. These results suggest a role for policy to increase the supply of clean inventors. They also emphasize the need for further research to understand better what drives individuals to become clean inventors and what policies could help produce more 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 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. 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.

5. Acemoglu et al. (2019) 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.

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 Acemoglu et al. (2019) and Popp et al. (2022a), 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 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

6. We use codes from the Cooperative Patent Classification and the International Patent Classification 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.

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 873,256 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, 30% 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] By contrast, the share of energy inventors who are active in both clean and dirty or grey energy patenting is only 10%.

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

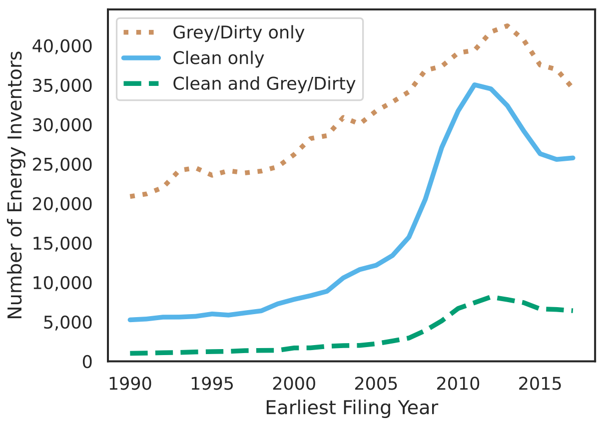
8. Li et al. (2014) provides disambiguated identifiers for USPTO inventors only. Our study requires disambiguation of all inventors globally.

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

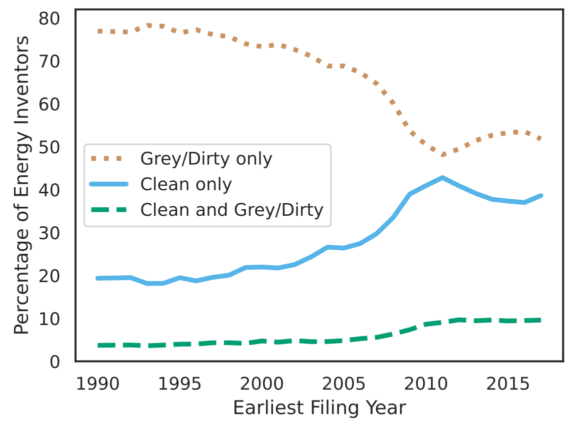
10. We limit our geographic scope because natural gas price data is available for OECD countries only.

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 patent in other non-energy fields.

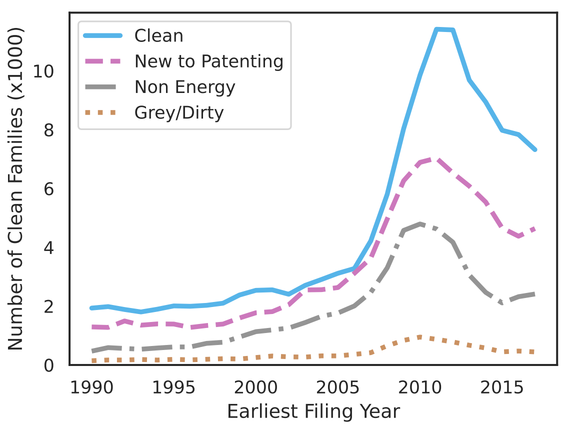
the 2000s. During that period, the share of inventors working in clean energy roughly doubled. On the other hand, the number of inventors working on dirty and/or grey energy grew more gradually over time, so that their share fell significantly over the 2000s. Finally, while the number of inventors working in both areas has increased over time, it remains small relative to the clean and dirty categories.



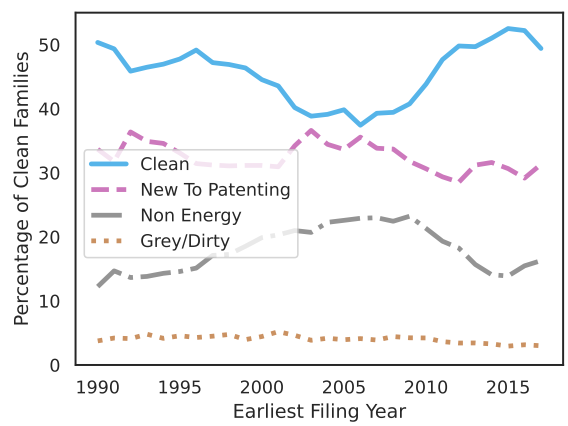
(a) Energy Inventors by Type (Levels)



(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. 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.

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 (46%) are from clean incumbents, either inventors with prior patenting in clean only (30%) or in clean as well as grey and/or dirty (16%). Roughly one-third of families (32%) 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]

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.

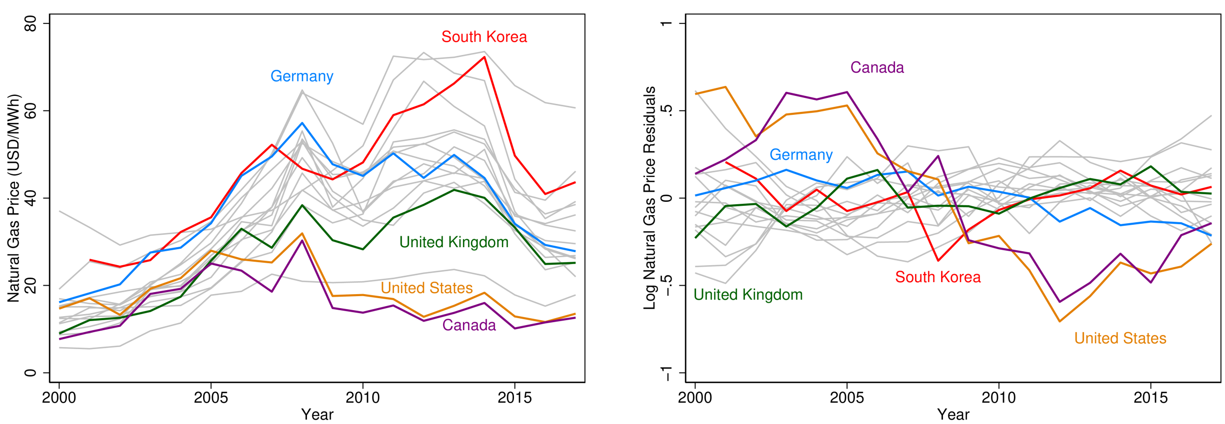
3.1 Identifying Variation

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

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

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.



(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.

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.

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 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]

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:

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

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).

where PAT^C_{it} 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]

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

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 F.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. Independent "garage" inventors who are not associated with any firms represent 16% of individual inventors in the data. For these inventors, we use the price of their country of residence.

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). 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 include 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.

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.[22] We use these data to estimate a firm-level model analogous to the inventor-level model in equation 1:

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

20. We use observations across all years to construct these shares because 71% of inventors do not patent before 2000.

21. We use observations across all years to construct these shares because 65% of firms do not apply for patents prior to 2000. Our results are robust to using pre-period patenting, which mitigates concerns about the potential endogeneity of the shares. See Online Appendix F.5 for details.

22. 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.

where E^k_{jt} is the number of new entrant inventors of type k filing a clean family with firm j in year t.[23] 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. P_{jt-1} is the price of natural gas that firm j is exposed to in year $t-1$ and X_{jt-1} include GDP per capita, energy, and low-carbon public RD&D spending that firm j is exposed to in year $t-1$. These variables are constructed as described in Section 3.2. Year and firm fixed effects are denoted γ^k_t and η^k_j, and u^k_{jt} is an error term. We estimate these models separately by type.

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.[24] 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.[25] 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).[26]

In Panel A, all six specifications yield output elasticities of around 0.5. The effect is somewhat larger when families are weighted by citations, indicating that price variation affects the production

23. 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.

24. We document results with additional outcome variables in Online Appendix F.3.

25. 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.

26. 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.

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)	0.548	0.463	0.635	0.533	0.468	0.389
	(0.037)	(0.037)	(0.047)	(0.048)	(0.047)	(0.047)
Inventors	110,454	110,454	110,454	110,454	110,454	110,454
Observations	763,630	763,630	763,630	763,630	763,630	763,630
Pseudo-R2	0.285	0.286	0.369	0.371	0.261	0.262
Panel B: Instrumental variable estimates						
Prices (log, t-1)	0.512	0.299	0.963	0.703	0.360	0.162
	(0.069)	(0.071)	(0.081)	(0.084)	(0.085)	(0.087)
Inventors	110,454	110,454	110,454	110,454	110,454	110,454
Observations	763,630	763,630	763,630	763,630	763,630	763,630
First-stage F-statistic	163	163	163	163	163	163
Panel C: Distributed lag estimates						
Cumulative effect (3 lags)	0.642	0.546	0.652	0.565	0.622	0.511
	(0.050)	(0.052)	(0.069)	(0.070)	(0.057)	(0.061)
Inventors	85,905	85,905	85,905	85,905	85,905	85,905
Observations	590,767	590,767	590,767	590,767	590,767	590,767
Pseudo-R2	0.289	0.290	0.366	0.367	0.264	0.265
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.

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.[27] The shale gas revolution generated a large decline in natural gas prices in North America that was expected to persist far 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 quite consistent across columns. The cumulative effect estimates for the citation-weighted outcomes lie in between the estimates from Panels A and B. This is consistent with the transient versus persistent nature of the price variation explaining the differences between the baseline and instrumental variable estimates. Given this, 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.[28]

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 estimate is largest for new inventors who had not previously patented. In Panel B, the estimates for new-to-patenting and

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

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

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.

TABLE 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)	0.258	0.167	0.044
	(0.110)	(0.096)	(0.127)
Firms	3,933	4,993	4,912
Observations	53,921	67,617	66,541
Pseudo-R2	0.692	0.605	0.643
Panel B: Distributed lag estimates			
Cumulative effect (3 lags)	0.618	0.456	-0.062
	(0.166)	(0.124)	(0.181)
Firms	3,779	4,703	4,642
Observations	43,733	53,109	52,559
Pseudo-R2	0.699	0.605	0.647
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.[29] The extensive 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 H 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 negative and imprecisely estimated amount. In total, this represents a clean patenting increase of 26% relative to a scenario in which the baseline rate of clean patenting from 2014 had been constant over 10 years.

To assess the sensitivity of these results, we present analogous estimates using alternative specifications and samples in Online Appendix H.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.

29. 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.

TABLE 3
Predicted Impacts of Carbon Pricing on Clean Patenting

Source	**Patents**	**Share (%)**
Intensive margin response		
Incumbent inventors	48,234	71.2
	(5,758)	(5.7)
Extensive margin response		
Entry from grey/dirty	4,410	6.5
	(1,199)	(1.8)
Entry from non-energy	-760	-1.1
	(2,218)	(3.3)
Entry to patenting	15,839	23.4
	(4,255)	(5.3)
Total	67,724	100.0
	(7,590)	.

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 26% 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.

6 CONCLUSION

We draw two sets of conclusions from the empirical evidence in this paper. First, inventors are highly specialized: most inventors patenting in electricity generation technologies work exclusively on either clean, grey, or dirty technology. About half of clean patents are produced by inventors with prior clean patents, and clean patenting output by these inventors is fairly responsive to changes in natural gas prices.

Second, new entrants play an important role in clean innovation: half of clean patents come from inventors who had not previously produced a clean patent. But perhaps surprisingly, we find that entry by these inventors does not respond strongly to variation in natural gas prices, particularly for inventors with a prior patenting history outside of energy.

Consequently, our analysis of carbon pricing shows that induced innovation is driven primarily by intensive margin increases in the patenting output of incumbent inventors. 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 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. In particular, our finding that induced innovation relies primarily on the intensive margin highlights the need for further work to understand better what drives individuals to become clean inventors and what specific policies could help produce more clean inventors.

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