Unintended Consequences of Tech-Neutrality: Evidence from Environmental and Innovation Policy Interactions

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Abstract

This paper studies how the interaction of environmental policy and technology-neutral R&D subsidies impacts the direction of innovation and finds surprising unintended consequences: tax credits for R&D undermine the directional effects of carbon taxes on patenting in low-carbon ("clean") versus "dirty" technologies by industrial firms in the United Kingdom. While economic theory suggests that innovation policy should be technology-neutral in the absence of other market failures, not all innovations are created equal, and some are characterized by a "double-externality" challenge whereby both the public nature of innovation as well as production or consumption externalities can impact the incentives firms have to innovate. Exploiting a discontinuity in the UK's R&D tax credit generosity, we estimate the difference in carbon price effects at the tax credit threshold to capture the interaction, allowing the effects to also vary for firms in industries directly exposed to the carbon tax versus not. We find that a £1 increase in the carbon price induces a 10% increase in R&D expenditures for firms directly exposed relative to those that are not, but the effect is 42% lower firms receiving more generous R&D tax credits. Carbon pricing also enhances clean patenting and reduces dirty patenting, but R&D tax credits attenuate these effects by 33%. Additional tests point to intra-firm path dependence as the mechanism, consistent with how technological progress is an endogenous process that is inherently not neutral. Our findings suggest that tech-neutrality can inadvertently change the composition of innovation by undermining other policies and has adverse effects when the objective is not just to increase the *level* of innovation but also to steer its *direction*.

Keywords: innovation; carbon tax; research and development (R&D); policy interactions

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1 Introduction

Fostering innovation is of first-order importance for economics and policy. Innovation is a critical driver of economic growth, but as inventors cannot fully capture the value of their innovations due to knowledge spillovers and the other social benefits that emerge (Nelson 1959; Arrow 1962), firms might under-invest in it. This market failure provides convincing rationale for public expenditures on private R&D. Understanding the form in which these policies and programs should take, though, is non-trivial, and doing so is increasingly urgent amidst the productivity growth declines in advanced economies since the 1970s along with widespread poverty in developing countries, and many governments are currently revisiting their innovation and industrial policies.

One feature that economists and policymakers do often promote is tech-neutrality—that innovation policy should remain as agnostic as possible towards the specific technologies or solutions to a problem based on the premise that favoring some might stifle competition. Tech-neutrality has indeed become a prominent characteristic of innovation policy. While some support schemes target specific problems and potential solutions—especially grant funding programs—governments globally also spend hundreds of billions of dollars every year on R&D tax incentives that firms in any industry and those investing in any type of technology can claim. And this form of support has been steadily increasing relative to direct funding over the last decade (OECD 2022).

At the same time, some innovations impact social welfare more than others, as they can be characterized by additional consumption or production externalities, so economic theory also suggests that policy should be more targeted in some cases to address the additional market failures. For example, society currently faces large-scale threats to humanity, like climate change and health crises, and innovation in technologies or new processes and practices to address them or mitigate their consequences comes with greater social benefits than innovation in other spaces. Policymakers may therefore rightly aim to not just increase the overall level or *rate* of innovation but to also steer its *direction*. After all, the survival of society and organizations producing the scientific knowledge that shape its resilience ultimately hinges upon the ability of science to pivot.

In this paper, we argue and show that tech-neutral innovation policy can have unintended consequences for the direction of innovation, not just because it might support innovation that does not contribute the most to social welfare but because it undermines policy instruments that do. Innovation that can address the world's most pressing problems tends to be characterized by a "double-externality" challenge, whereby production or consumption externalities affect the incentive to innovate in addition to imperfect appropribility. For example, clean energy technologies reduce pollution and vaccines reduce the spread of disease, and firms may under-invest in them when prices do not reflect these benefits. Taxes and subsidies are thus common tools for addressing these externalities, and they can, in theory, redirect innovation towards specific goods and services through a market pull channel.[1] Interventions like these and government support for R&D are often framed as complementary tools for spurring innovation. Carbon taxes increase the price of dirty energy relative to clean, which can increase demand for clean energy and induce innovation in low-carbon technologies, for instance. Likewise, subsidies that reduce the price of vaccines or education, reducing uncertainty about future demand. Subsidies for R&D could then enhance the effects on the incentive to innovate by reducing the cost of investing in R&D.

But when R&D subsidies are entirely tech-neutral, firms could alternatively use the funding to support their status quo innovation activities or efforts that do not involve pivoting.[2] And sticking with the status quo may be the more likely choice given the path dependent nature of innovation. Technological choice is an endogenous process that depends on knowledge endowments and technology performance such that historical patterns determine future technological change (Dosi 1988; Redding 2002; Acemoglu, Akcigit and Kerr 2016a). It is cheaper and easier for firms to build upon their own existing knowledge or to assimilate knowledge created by others due to the role of learning and absorptive capacity (Cohen and Levinthal 1989). Tech-neutral policy therefore may not really be tech-neutral because the innovation process itself is inherently not neutral. Rather, it may favor incumbent technologies and industries and thus dampen the potential effects of taxes and subsidies on the direction of innovation rather than enhance them.

We empirically explore this relationship by estimating the effects of carbon pricing, tech-neutral R&D tax credits, and the interaction of the two policy instruments on firms' R&D expenditures and patenting in low-carbon energy and climate change mitigation technologies versus dirty innovation. Examining the interaction is particularly important because of how both policy instruments impact a shared outcome. We study firms in the UK, which is a particularly important and interesting country to study in the context of tech-neutral innovation policy, as tax relief makes up the vast majority of its government support for business expenditures on R&D (BERD). Across all OECD

[1] Note that while these can have a directional influence, they remain tech-neutral in terms of the actual technology developed or used for addressing the externalities.

[2] When we refer to changing the direction of innovation, this could be a matter of transitioning from innovation in specific technologies, or it also could be a matter of directing innovation towards solutions that both can address a market failure but to different degrees, like fundamental advances in the ways in which education systems are structured as opposed to more incremental changes like flipping classrooms.

countries, it provides the most support for business R&D via tax incentives as a percentage of GDP (OECD 2022). We also focus on firms in pollution-intensive industries that are notoriously difficult to decarbonize, like manufacturing and mining, as well as the power sector.

We implement a “difference-in-difference-in-discontinuities” research design to identify the interaction effect between carbon pricing and R&D tax credits. Exploiting a discontinuity in the generosity of R&D tax credits whereby firms under policy-defined size thresholds benefit from more generous rates than those over them, we estimate the effect of carbon prices generated by the EU-Emissions Trading Scheme (ETS) on R&D and patenting and interpret the difference in effects at the threshold as the interaction effect.[3] Carbon prices from the EU-ETS are plausibly exogenous for UK firms, as they are determined by trades on an international market and UK firms do not have sufficient market power to influence them. Furthermore, only a subset of firms are regulated by the EU-ETS, so we allow the carbon price effects at the tax credit threshold to vary based on whether the firm is in a regulated industry. Regulated industries are not selected at random, though, so we control for how industries differ and how they change differently over time. The results can be interpreted as effects relative to firms in unregulated industries. Our approach thus relies on three sources of variation: differences in tax credit generosity rates determined by policy-defined firm size thresholds, changes in carbon prices over time, and whether a firm is in an industry regulated by the EU-ETS (i.e., those that are directly “exposed” to carbon prices).

The results are quite striking. While even just a £1 increase in the carbon price induces approximately a 10% increase in R&D for firms regulated by the EU-ETS (and thus directly exposed to carbon pricing) relative to those that are not regulated,[4] the effect decreases by 42% for firms receiving more generous R&D tax credits. This translates into a reduction in the elasticity of R&D with respect to carbon pricing from 0.65 to 0.38. When examining patenting behavior, we find that the policy interactions also have consequences for the direction of innovation. A £1 increase in the carbon price induces a 0.9% increase in clean patenting by firms regulated by the EU-ETS relative to those that are not regulated. The elasticity of low-carbon patenting with respect to carbon pricing is 0.653. Receiving more generous R&D tax credits dampens the effect such that the elasticity decreases by 33% for regulated firms with lower tax credit benefits relative to unregulated firms. On the contrary, a £1 increase in the carbon price reduces patenting in “dirty” technologies by 0.3%, further enhancing the directional effect of carbon pricing. But there

[3] As described later, the eligibility for the more generous tax credits depends on the firm's number of employees, total assets, and turnover.

[4] In level terms, this is similar to the findings in Calel (2020).

is no interaction effect with R&D tax credits, which is expected given that there is no increase in dirty patenting in the first place.

These effects may seem small but they are economically meaningful when considering how much it would cost to generate these outcomes through other policy tools. The effects also reflect behavior induced by just small changes in the carbon price, and patenting is rare in general. If we were to assume a carbon price of £50 per ton of CO2, which is higher than it was throughout our sample period but much lower than the most recent estimates of the social cost of carbon,[5] and if we make the (albeit strong) assumption that the effects can be extrapolated linearly and homogenously across regulated firms, the results would imply that a £50 carbon price would generate between 44 to 61 additional low-carbon patents. This is also similar to the results in Calel (2020), which indicate that UK firms produced about 64 additional low-carbon patents between 2005 and 2012 due to the EU-ETS. To put these numbers into context, Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen (2022) find that £1 million in public expenditures via the UK's R&D tax credit scheme yield 1.12 additional patents. Creating 44 to 61 would patents would thus cost between £39 and £54 million as opposed to generating billions in revenue through the EU-ETS.

We also explore the mechanisms behind these findings. There is no exit or reallocation of inputs but there is significant path dependence in firms' direction of innovation. The effects we estimate in general are within-firm, and by constructing measures of firm- and market-level knowledge stocks, we find that they are enhanced by firms' own knowledge endowments as opposed to spillovers from other firms' patents. Carbon pricing seems to induce firms to pivot in their scientific research as opposed to just increasing the overall level of clean innovation throughout the economy while maintaining similar levels of dirty innovation.

Our findings suggest that tech-neutral R&D tax credits inadvertently change the composition of innovation by favoring incumbent technologies and undermining the directional effects of carbon pricing, raising questions about the conventional wisdom that innovation policy should always be tech-neutral. When the incentives to innovate are not just affected by knowledge spillovers but also other externalities, and when other policies aim to address these market failures, tech-neutral innovation subsidies might have unintended consequences for the direction of innovation. Tech-neutral innovation policy therefore may not always be tech-neutral in practice since technological progress itself is not tech-neutral. Tech-neutrality has also become a staple in other fields of

[5] Rennert, Errickson, Prest, Rennels, Newell, Pizer, Kingdon, Wingenroth, Cooke, Parthum, Smith, Cromar, Diaz, Moore, Muller, Plevin, Raftery, Sevcikova, Sheets, Stock, Tan, Watson and Anthoff (2022) find that it is currently about $185 per ton of CO2.

economics, so our paper may be of interest when designing policy in those settings as well.[6]

Understanding how policy can steer the direction of innovation is not just important for satisfying policymakers' interests—it is also well-justified by economic theory, as some innovations can contribute more to social welfare than others. Many of those that can address the world's most pressing challenges are characterized by the “double-externality” challenge. Multiple market failures tends to call for multiple interventions, but when both affect a shared outcome, it is important to consider their interaction. Studying this phenomenon in the context of low-carbon technologies is particularly important given the tremendous socioeconomic costs created by climate change. The existence of both market failures in the energy and environmental innovation context has been discussed in the literature conceptually (Jaffe, Newell and Stavins 2005), and the endogenous technological change literature has started to study the optimal policy mix, but there has been little attention to it empirically.

Our paper thus marries the literature studying whether energy and environmental policies and regulations foster green innovation to the literature that evaluates broader innovation tax incentives and subsidy schemes. There is growing empirical evidence that carbon taxation can help steer the direction of innovation towards those that protect environmental systems (Popp 2002; Martin, De Preux and Wagner 2014; Calel and Dechezlepretre 2016; Aghion, Dechezleprêtre, Hemous and Martin 2016; Calel 2020). Likewise, there is increasing evidence suggesting that both direct grants and fiscal incentives supporting innovative activity enhance R&D expenditures and innovation outputs (Einiö 2014; Bronzini and Iachini 2014; Bøler, Moxnes and Ulltveit-Moe 2015; Howell 2017; Azoulay, Graff Zivin, Li and Sampat 2018; Guceri and Liu 2019; Agrawal, Rosell and Simcoe 2020; Dechezleprêtre et al. 2022; Pless 2022). Our findings highlight the importance of understanding how their interactions impact firm behavior when the objective is not just to increase the level of innovation across the economy but also its direction.

We also contribute to the literature on path dependence in technological progress. While the cumulative nature of innovation has been recognized for a long time (Rosenberg 1976), basic science is increasingly shaping the direction of innovation and intensifying the process (Galasso and Schankerman 2015). Path dependence is also at the heart of endogenous growth models (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1992; Acemoglu 1998) and the directed technical change literature studying innovation in the environmental and climate change context (Acemoglu,

[6] For example, it has played a prominent role in auction theory (Klemperer 2010), and from an economic regulatory perspective, it plays a role in determining how to efficiently procure goods or services when choosing between multiple technologies (Fabra and Montero 2022).

Aghion, Bursztyn and Hemous 2012; Acemoglu, Akcigit, Hanley and Kerr 2016b; Aghion et al. 2016). Most of this work is theoretical with the exception of Aghion et al. (2016) who estimate the effects of knowledge stocks on clean and dirty innovation in the transportation sector. We complement these papers by showing that path dependence can affect the direction of innovation not just directly but also indirectly through policy instruments targeting other externalities.

Developing a better understanding of how to design innovation policies is of first-order importance and increasingly urgent. Governments in many countries are currently reviving their innovation and industrial policies, and support for research and development (R&D) is playing a prominent role.[7] Nations are also battling large-scale threats to humanity and the economy, such as climate change and inadequate healthcare services. Steering the direction of innovation towards that which can address these challenges is just as important, if not more, than increasing the overall level of innovation. After all, the survival and progress of society and the organizations that shape such resilience ultimately hinge upon the ability of science to adapt. The capacity for organizations to pivot in their scientific research pursuits is not yet well-understood, but recent research is finding that it can be costly for scientists to switch directions (Azoulay, Fons-Rosen and Graff Zivin 2019; Deming and Noray 2020; Myers 2020; Hill, Yin, Stein, Wang and Jones 2021). Our paper provides new insights for this nascent body of work.

The rest of this paper is organized as follows. Section 2 provides background on our empirical setting and the policies that we study. Section 3 details our estimation strategy. In Section 4 we describe our data, and in Section 5 we conduct a series of tests to explore our research design's identifying assumptions. Our main results are presented in Section 6. We explore the underlying mechanism in Section 7 and conclude in Section 8.

2 Policy Background and Institutional Setting

Our empirical setting for examining tax credit and carbon pricing interactions is the United Kingdom, focusing on firms in pollution-intensive sectors, like steel, cement, petroleum, electricity, plastics, and more. In this section, we describe the two policy mechanisms that we study—carbon pricing under the EU-ETS and a technology-neutral R&D tax credit—and the ways in which they affect firm incentives.

[7] For example, President Biden's budget request for FY2023 included 205 billion USD for Federal R&D, an all-time high and 28% increase over FY2021. The UK's 2017 Industrial Strategy also set a target of increasing overall UK investment in R&D to 2.4% of GDP by 2027.

2.1 Carbon Pricing in the UK

The European Union's Emissions Trading Scheme (EU-ETS), the world's first major and still largest carbon market, is a cap-and-trade scheme introduced in 2005 that places a cap on the total amount of greenhouse gases that can be emitted by all “regulated” firms. The scheme covers the most pollution-intensive industries in the power and manufacturing sectors—like iron, steel, petroleum, chemicals, cement, and more—as well as airlines. The idea is that, if a regulated firm's emissions exceed what the allowances permit, it must purchase additional allowances from others, but if the firm finds ways to reduce its emissions, it can sell the remaining credits. The market thus generates a carbon price and creates incentives for firms to reduce their emissions. Although the EU-ETS was introduced in 2005, carbon pricing in the UK has operated primarily through the EU-ETS since about 2008. Britain already had other carbon pricing policies in place, so there was a transition period as plants participating in the UK ETS were exempted from the EU-ETS until 2007 and those covered by Climate Change Agreements were exempted until 2008.

Firms have two general paths to take to reduce their pollution levels—they can either adopt abatement technologies or they can innovate by developing low-carbon technologies or reformulating their processes and practices in ways that reduce their emissions, such as by improving input and output efficiency. The former moves firms along their marginal abatement cost curve whereas the latter expands the firm's technology set, shifting the marginal abatement cost curve inward. Firms that innovate thus benefit from lower abatement costs. Some forms of innovation like improvements to processes and practices also could translate into the use of fewer inputs and lower a firm's costs.

2.2 R&D Tax Credits in the UK

The UK government introduced its first fiscal incentive scheme aimed specifically at fostering innovation in the year 2000: the R&D Corporation Tax Relief scheme. The scheme is entirely technology-neutral such that firms across all sectors can benefit from it. It has become increasingly generous over the past two decades and is now the main source of government support for private sector R&D. Figure ?? plots government support for business R&D as a percentage of GDP for the UK (Panel A) and all OECD countries (Panel B) from 2000 to 2018. Expenditures via tax credits represented just 3 to 5 percent of total government spending on business R&D through about 2006 compared to 29 percent in 2018. Similar patterns can be seen for the OECD as a whole. Government support for innovation in general has been increasingly steadily in the UK since 2012, and more recent policy priorities suggest that this trend will continue exponentially.[8]

The UK's tax relief scheme is a volume-based tax allowance that reduces rms' corporate tax liabilities on taxable income based on their R&D expenditures. Qualifying R&D expenditures primarily include labor costs as opposed to capital investments, and such labor expenditures must relate to e orts to develop new processes or products or improve existing ones. The scheme sets enhanced deduction rates, which are essentially multipliers applied to current R&D expenditures to determine the amount that can be deducted. Much higher enhanced deduction rates apply for small and medium enterprises (SMEs) relative to larger rms, and they have increased over time from 150% in the program's early years to 225% in 2012 and to 230% by 2017. Loss-making SMEs can also claim a refundable tax rebate. The total tax credit \bene t" as a percentage of the rm's R&D expenditures is a function of (i) the rm's R&D expenditure, (ii) the rate at which its pro ts are ordinarily taxed, and (iii) whether it is loss-making.

For the purposes of the R&D tax credit, SMEs are de ned using di erent rm size thresholds than those that de ne SMEs for all other intents in puroses in the UK and Europe more broadly. In all other cases, rms must have fewer than 250 employees and either less than 43 million euros in total assets or less than 50 million euros in sales to be considered a SME. This was also the de nition used by the R&D tax credit when it was rst introduced. In 2008, though, the UK government increased these thresholds for the R&D tax credit scheme such that rms with fewer than 500 employees and either less than 86 million in total assets or 100 million euro in sales sales now qualify for the more generous tax credit.

Appendix Table B.1 speci es these enhanced deduction rates and the nal bene t amounts (henceforth \tax credits") as a percentage of R&D expenditures that they equate to under di erent conditions. Tax credits ranged from about 21 percent to 26 percent since 2008. For comparison, the enhancement rate for larger rms|those just over the SME rm size thresholds|has been consistently 130 percent, translating into tax credit rates that have declined from 8.4 percent in 2008 to about 6 percent more recently.[9] Bene ts for SMEs are about 17 percentage points and 7.6 percent higher than larger rms on average over the sample period.

[8] Government spending on R&D was 0.7% of GDP as of 2020 in the UK and they recently set a target of increasing spending to 2.4% of GDP by 2027.

[9] The decline is due to decreasing corporate tax rates over the sample period.

3 Empirical Strategy

Our main objective is to estimate the causal interaction effects of R&D tax credits and carbon pricing on firms' R&D expenditures and patenting activity. To do so, we develop a "discontinuity-in-effects" research design that adopts features of the more familiar difference-in-discontinuities approach but diverges slightly given the sources of variation that we exploit. Our method entails using the sharp discontinuity in R&D tax credit rates described in Section 2 to not only identify the direct effect of more generous tax credits (as would be the case in a standard regression design (RDD) framework) but also for the interaction effects, estimating the effect of carbon pricing on each side of the tax credit threshold and taking the difference in the carbon price effects for firms within a narrow window around the threshold as the interaction effect. We are therefore estimating a discontinuity in the carbon price effects (rather than a difference in a discontinuity).

We estimate this in one step using various specifications of the following general form:

$$
\begin{aligned}
Y_{it} = {} & \beta_1(CP_t \times TC_{it} \times R_i) + \beta_2(CP_t \times R_{it}) + \beta_3(CP_t \times TC_i) + \beta_4(TC_{it} \times R_i) \\
& + \beta_5 CP_t + \beta_6 R_i + TC_{it}(\beta_7 + \beta_8 A_i) + \beta_9 A_i + X_{it} + \varepsilon_{it};
\end{aligned} \tag{1}
$$

where Y_{it} is the outcome variable for firm i in year t, CP_t is the average carbon price in year t, and R_i is an indicator equal to one if the firm operates in an industry directly regulated under the EU-ETS (see Appendix Table ?? for the list of regulated industries as well as unregulated industries that we include in our sample).[10] We set the indicator for tax credit treatment status, TC_{it}, equal to one if firm i's (lagged) employment is less than 500 employees in year t and either their (lagged) turnover or total assets is less than 100m GBP or 86m GBP, respectively.[11] We estimate local linear regressions around the running variable cutoff and restrict the sample to $A_{it} \in [A_c - h; A_c + h]$, where h represents different windows around the threshold.[12]

Our main coefficients of interest are β_1 and β_2. Firstly, β_2 represents the carbon price effect for firms in industries that are regulated by the EU-ETS but do not benefit from the more generous

[10] We include firms that are not in directly regulated industries but are in industries that might be indirectly affected by carbon prices due to its effects on inputs and end-use products, but we do not focus on estimating the effects of carbon pricing on these firms due to the importance of including various sets of fixed effects that absorb the effect.

[11] We view this as a sharp discontinuity approach, therefore, despite treatment being based on multiple running variables, in that we estimate the effect of the binding criteria (based on employees) conditional on meeting the criteria for the other two variables.

[12] Even though the policy was introduced in 2008, firms were required to provide proof of qualifying as a SME based on two years of balance sheet data, so 2010 was the first year in which we can be sure firms were responding to the policy.

relative to unregulated firms (that do not benefit from more generous tax credits either). Carbon prices are exogenous to UK firms' input choices and innovation efforts given that they are determined by trades in an international market and UK firms likely do not hold enough market power to influence prices, so we do not need an instrument for carbon prices to identify their effect. The way in which more generous tax credits impact the marginal effect of carbon pricing on regulated firms' outcomes is captured by β_1. If $\beta_1 < 0$, accessing more generous tax credits dampens the marginal effect of carbon pricing, and it enhances it if $\beta_1 > 0$.[13] To get the total effects of each policy on firms regulated by the EU-ETS, one would sum the coefficients associated with terms that include those elements. We discuss this further when describing our results in Section 6.

Although we define treatment status precisely using all three eligibility criteria, we use lagged employment as the running variable since it is the binding treatment status determinant. We normalize the running variable function, $\tilde{A}_i = A_i - A_c$, at the 500 employee cutoff point, allowing its slope to differ on each side of the cutoff, and ε_i is the random error. Additional control variables included in the matrix X_{it} include firm fixed effects to control for unobserved firm characteristics that might be correlated with innovation effort and outcomes, such as management quality, and year fixed effects to control for macro-economic shocks and general trends in technological opportunities. While we cannot include industry-year fixed effects because they would absorb β_2, we include industry-year linear trends, which account for how industries might change differentially over time but which impose stronger assumptions on the functional form of such trends relative to industry-year fixed effects. In most of our baseline regressions, we use triangular weights (i.e., observations are assigned larger weights when firm size is closer to the 500 employee threshold) and cluster standard errors at the industry level to adjust for potential serial correlation in the errors.

Our approach differs from simply estimating the heterogeneous effects of carbon pricing in that the differences in carbon price effects are driven by an exogenous source of variation—the discontinuity in R&D tax credit generosity—as opposed to endogeneous firm characteristics. The validity of this research design rests upon five main identification assumptions that we investigate in Section 5: 1) the firm size thresholds determining tax credit generosity were not endogenously determined by firm characteristics, 2) the running variable—number of employees—is not manipulated around the threshold, 3) the R&D tax credit is relevant and actually induces innovative activity (when considered on its own), 4) there are no other policies that create incentives that vary sharply at

[13] In theory, one could recover the effect of carbon pricing on unregulated firms (β_5) and its interaction with tax credits (β_3), but the sets of fixed effects we include in our main specifications absorb β_5. The results we present therefore capture the effects on firms in industries regulated by the EU-ETS relative to those that are not regulated.

the same thresholds, 5) the EU-ETS carbon prices are exogenous for UK rms

4 Data and Summary Statistics

In this section, we describe the three main sources of data that we merge and use throughout the analysis as well as our method for classifying patents as being low-carbon innovations (henceforth \clean" patents) or innovations that further facilitate polluting activities (henceforth \dirty" patents). We also provide summary statistics for our nal sample.

4.1 Firm-Level Balance Sheets

We start with Bureau van Dijk's (BvD) Financial Analysis Made Easy (FAME) database to gather rm-level balance sheet and ownership information. This provides us with variables such as employment, total assets, and turnover, which are required for determining whether a rm is eligible for more generous RD tax credits, as well as our main R&D spending variable. It also includes other nancial and production details, like labor and capital, that we use throughout the analysis. We follow the standard protocols to prepare the FAME data, such as de ning the current year as the one associated with the latest account date if the month is June or later of that year and the preceding year otherwise. We convert nominal monetary gures into real 2010 GBP and turnover and total assets into Euros for assessing tax credit eligibility. We drop duplicates and cases for which there are obvious errors in our key nancial variables of interest.[14]

4.2 Carbon Prices

For our carbon price variable, we use ICE Market Data to obtain daily data from the European Climate Exchange (ECX), which is the largest EUA trading venue, capturing two-thirds of total traded volume (Mizrach et al 2014). We use the annual average of daily one-month ahead futures price. The vast majority of EUA trades happen in the futures market rather than the spot market, making the futures market more relevant for price discovery and rm behavior.

Figure I plots the carbon price from 2005-2019 (real 2010 GBPs), which exhibits signi cant variation over the EU-ETS lifetime due to various market factors. After the scheme's initiation in 2005, the carbon price plummeted to just over 5 GBP on average in 2006 (having reached nearly 30 euros during the year), which has been attributed to emissions being lower than the amount of

[14] For example, we drop 3 and 11 observations with negative R&D expenditures and turnover data, respectively.

permits originally allocated. The ETS entered its second trading phase from 2008-2012, and since permits could not be carried over, the market had a fresh start. Prices climbed again at first but then dropped substantially amidst the global financial crisis and a decline in polluting economic activity (i.e., there was less demand for permits). The third trading phase began in 2013 as more sectors were added while the number of permits was reduced, although the price remained low due to oversupply. Policymakers introduced reforms around 2015-16 though, such as a market stability reserve that would start in 2019, and the price steady rose again in response, hitting a record high.

[FIGURE I HERE]

4.3 Patents and Technology Classifications

While R&D expenditures measure one innovation input fairly cleanly, capturing innovation output can be challenging. Albeit imperfect, patenting has been the most commonly used proxy in the literature so far, as they are arguably reasonable proxies for a firm's efforts to expand the technology set. They also offer the advantage of allowing us to identify low-carbon innovations and explore the direction of innovation. We draw patent data from the World Patent Statistical Database (PATSTAT), which is maintained by the European Patent Office. We extract all patents filed by all organizations located in Great Britain and compile patent characteristics such as forward and backward citations, earliest filing date of the application, and whether the patent (or patent family) was actually granted.

To identify low-carbon patents, we follow the patent class system recently developed by the European Patent Office (EPO), whereby technology experts and patent examiners tag all patents related to climate change mitigation in the production or processing of goods (the Y02 class). The class includes technologies that could directly reduce greenhouse gas emissions, such as through combined heat and power, carbon capture and storage, or renewable energy generation (and the integration thereof into buildings, etc.). It also includes innovation related to advanced energy management and advanced computing for monitoring or controlling equipment for energy generation units. We further enhance our "clean" categorization by also including patents outside of this class that are associated with air pollution abatement from stationary sources, which include both post-combustion technologies (e.g., the purification of waste gases) and integrated technologies (e.g., removal of waste gases).[15]

[15] We use the OECD's classification for these following Annex Table 1.1 in OECD (2016).

Rather than compare low-carbon patenting to just all other technologies, we also identify "dirty" patents, as this will allow us to examine not just whether clean innovation increases but also whether dirty innovation decreases in response to the policies. We start by using the classification recently developed by the EPO and International Energy Agency for identifying fossil fuel supply-related technologies (see IEA (2021)). They cover technologies that contribute to exploration, extraction, and transformation of fossil fuels as well as the delivery of such products to end users. For example, these include those related to oil refining and gas conditioning.[16] Technologies that could improve combustion devices and energy-related uses of fossil fuels are not included given the overlap with "clean," as they could reduce greenhouse gas emissions, so our definition of dirty is very strictly "dirty." We further enhance our sample of "dirty" patents by including those related to hydraulic fracturing—which revolutionized the natural gas industry in the late 2000s—following the classifications detailed in Popp et al. (2020).

To measure innovation, we construct several measures using the patent data, paying particularly close attention to patent quality given the significant heterogeneity in patent value and how many are of very low value. We start by finding the number of patent families associated with each firm-year. There can be multiple patent filings associated with an invention (a patent family), so we follow Aghion et al. (2016) and consider all filings within a patent family as being associated with just one innovation, and we assign the patent family to the year associated with the earliest application date of filings within the patent family. We only include patent families that are eventually granted as an initial step towards eliminating low-quality patents.

Next, since multiple firms may contribute to an invention, we weight each patent family assuming even contributions per firm within patent family. For example, if two firms patented within a patent family, each firm is assigned a 0.5 for contributing half of the effort towards the invention rather than a 1. This helps avoid double-counting and accounts for varying degrees of effort firms put towards innovation. We then weight each of these "contributions" by the patent family's forward citations to proxy for quality. Lastly, we aggregate the data to the firm-year level by summing the contributions each firm makes to inventions each year, which we refer to as "patent counts" moving forward, and the contributions weighted by forward citations, which we refer to as "quality-adjusted patents."

[16] More specifically, these include innovations like the modification of chemical composition of gases to produce an improved fuel.

4.4 Baseline Sample and Summary Statistics

Our final merged and cleaned data set contains 619,763 observations for 45,478 unique firms from 2000 to 2019. In our main analyses, we study only the period after which the new tax credit generosity thresholds were imposed (2010 through 2019).[17] This reduces the sample to 271,148 observations across 37,584 firms. Finally, we limit the sample to include only firms within narrow windows around the 500 employment tax credit threshold following a standard RDD. In our widest window using a bandwidth of 300 employees, our sample includes 4,211 observations across 797 firms from 2010 through 2019 that have between 200 and 800 employees. This reduces further to 2,129 observations across 437 unique firms in our narrowest sample including firms with 300 to 700 employees.

One of the more limiting characteristics of our data is that R&D expenditures are frequently not reported. In some cases, these could be interpreted as zeros, but we are not able to identify when they are truly zero as opposed to just missing. Luckily there are no reporting requirement differences around the 500 employee threshold that we use in our empirical strategy, which we discuss in more detail below in the context of our identification strategy.

Table I summarizes firm characteristics and R&D expenditures (Panel A) as well as patenting behavior (Patenting) for firms included in the sample with 200 to 800 employees. As expected, the firms are capital-intensive and spend about 3 percent of annual revenue on RD, which is consistent with expectations for these industries. Firms files about 0.290 patents (measured as patent families as described above) per year for any technology, which is consistent with what would be expected for these industries.[18] They file about 0.012 patents specifically related to climate change mitigation and clean energy technologies and 0.010 patents related to \dirty" manufacturing and energy inventions per year.

[TABLE I HERE]

[17] Although the policy was introduced in 2008, firms were required to provide proof of eligibility for the more generous tax credits for the two preceding years to qualify, so we consider 2010 to be the first post-policy year.

[18] In their study of similarly-sized firms, Dechezleprêtre et al. (2022) find that firms file between 0.62 to 0.71 patents per year for firms in all sectors. Firms in our sample do not include some of the most R&D-intensive industries within the economy, though, so we would expect our averages to be much lower.

5 Identification and Research Design Validity

Before moving to our main analysis, we explore the identification assumptions behind our research design. Our empirical approach essentially entails testing whether the marginal effect of carbon pricing on R&D and patenting differs based on the R&D tax credit's generosity, leveraging the discontinuity in tax credit generosity determined by firm size. Most of the conditions associated with this discontinuity-in-effects design therefore are similar to those in a standard RDD setting, and they must hold not only to identify the effect of the tax credit but also the interaction effect, since we estimate the interaction effect as the difference in carbon price effects at the threshold. In addition to the assumptions associated with these features, we also assume that EU-ETS carbon prices are exogenous for UK firms. We investigate these assumptions in the subsequent sub-sections.

5.1 Exogeneity of R&D Tax Credit Generosity Threshold

The first assumption is that the firm size threshold determining tax credit generosity is not endogenously determined by firm characteristics. If so, untreated firms (i.e., those with more than 500 employees) might be systematically different from treated firms just above the cutoff in ways that are correlated with innovation effort, making them a poor control group. This is not just important in the context of identifying the tax credit effect but also the interaction effect, since attributing differences in the carbon price effect to a difference in the tax credit rate relies upon the tax credit effect being identified in the first place.

We explore this by examining whether observable covariates are continuous across the threshold in the years prior to the tax credit policy imposing the 500 employee cutoff. Assigning firms that would have been treated under the new eligibility regime as treated in pre-policy years, and limiting the sample to include only firms around the size threshold, we estimate the "pseudo-treatment" effect on various firm characteristics within a regression discontinuity framework as follows:

$$C_i = \alpha_0 + \alpha_1 A_i + J_i(\beta_0 + \beta_1 A_i) + X_{it} + \varepsilon_i; \qquad (2)$$

where the treatment and running variables take on the same definition as before. The main coefficient of interest is β_0, capturing the difference in the observed covariate C_i for firms under the tax credit threshold relative to those over it. Because the sample includes only pre-policy years, though, those under the threshold do not actually receive higher tax credits, so we are estimating an artificially imposed "pseudo-treatment." The matrix X_{it} includes firm and industry-year fixed e ects. We use triangular weights and standard errors are clustered by industry.

The results are presented in Appendix Table B.2. There is no evidence of a discontinuity in (log) revenue (Column 1), capital (Column 2), or average wages (Column 3). In Columns 4 and 5, the dependent variables are indicators equal to one if operating cash and after-tax pro ts are positive, respectively, and there does not appear to be a discontinuity. These results suggest that rms around the tax credit generosity threshold are similar, and those under it could serve as a reasonable control group. It also suggests that the government did not select 500 employees as the threshold based on rm characteristics that re ect performance like these.

5.2 No Running Variable Manipulation

The second identifying assumption is that rms do not manipulate the running variable|number of employees|around the tax credit threshold. For example, rms might strategically downsize in response to the policy to take advantage of the more generous tax credits, and if so, rms below the threshold might di er systematically from those that are unobservable and correlated with innovation e ort. They might be particularly savvy, for example. This would make those above the threshold a poor control group.

We explore this by examining whether there is a spike in the density of rms at the 500 employee threshold in the post-policy years. In Appendix Figure C.5, we plot the distribution of rms by size in a histogram (Panel A) and in a scatter plot using third-order polynomial t (Panel B) for rms with 250 to 750 employees. There does not visually appear to be bunching just under the threshold, and the formal McCrary density test also does not provide evidence of such manipulation.[19] We also create analogous gures in Appendix Figure C.6 that use data only for the years 2013-2018 to ensure that such behavior did not evolve over time. There is also no evidence of bunching or downsizing in later years for rms in our sample.

5.3 R&D Tax Credit is E ective

The next assumption is that the R&D tax credit is relevant. If the tax credit itself does not induce innovative activity, then nding any di erences in the carbon price e ect at the threshold would likely just be by chance|an artifact of the data|rather than driven by the tax credit policy. Existing research on the tax credit e ects alone using quasi-experimental methods and administrative data suggests that the R&D tax credit policy has indeed \worked," having large,

[19] The log di erence in the density is -0.350 with a standard error of 0.300.

positive e ects on rm R&D expenditures and innovation outcomes like patents (Guceri and Liu 2019; Dechezleprêtre et al. 2022; Pless 2022). We complement these ndings with our own estimates to ensure that this is also the case for rms in our sample.

We start with a visualization of the discontinuity in R&D expenditures at the 500 employee threshold. In Figure II, we plot average R&D expenditures for bins of observations along the rm size distribution in the post-policy period and t a second-order polynomial. There appears to be a break at the threshold with R&D expenditures increasing by about 50,000 GBP for rms just under the threshold relative to those just over it. This is consistent with other ndings in the literature as well|for example, Dechezleprêtre et al. (2022) nd that R&D expenditures increased by at least 60,000 GBP (their lower bound estimate) in their quasi-experimental study of the UK's tax credit using administrative data.

[FIGURE II HERE]

Using (log) R&D expenditures as the outcome variable, we estimate the e ect of the tax credit in the post-policy period using di erent speci cations that follow the general form of Equation 2. The estimates presented in Appendix Table B.3 from models that include varying sets of xed e ects and window widths around the threshold indicate that the di erence in the tax credit rate at the threshold induces about a 40 to 47 percent increase in R&D expenditures. These e ects are smaller than others found in the literature|for example, ? nd that about an 80 percent increase using a slightly di erent research design and di erent data|so we interpret these results as lower bounds if anything.

5.4 No Confounding Policies

The research design also requires there to be no other policies generating di erent incentives for rms to innovate right at the rm size cuto . This assumption is satis ed to the best of our knowledge. The rm size thresholds determining tax credit generosity apply for R&D tax credit purposes only, thresholds that are double the size of those used to de ne SMEs for all other intents and purposes in the UK. Other policies in the UK that provide di erential bene ts based on rm size use much lower thresholds.

5.5 Exogeneity of Carbon Prices

When estimating the effects of carbon prices, we do so simply through OLS because the EU-ETS carbon price is plausibly exogenous in our setting. It is determined by trades across many countries and sectors, and because firms in the UK manufacturing and power sectors likely do not hold a lot of market power, they are price-takers. This is also the assumption in Fabra and Reguant (2014)'s study of emissions cost pass-through for Spain's electricity sector.

6 Main Results

6.1 Carbon Price Effects on R&D Spending

Before examining how the interactions of the two instruments affect R&D, we begin by estimating of carbon pricing on its own. This serves two main purposes: it allows us to compare our results for the total effect of carbon prices once we fully account for how they interact with the tax credits relative to what we would find if we were to ignore their interactions, and it allows us to compare our findings to others in the literature who have examined the effects of carbon taxes on innovation to provide confidence that any differences in effects that we find are not just driven by our identification strategy or data.

To examine the effect on its own, we assume carbon prices are exogenous to UK firms as described in the last section and estimate a simple OLS regression of R&D expenditures on the carbon price conditional on the fixed effects and controls that we ultimately use in our baseline regressions (firm, year, and industry fixed effects as well as industry-year linear trends). We limit the sample in similar ways as well, keeping only firms within a narrow window around the tax credit threshold and studying post-tax credit policy years (i.e., 2010 onward).

The results are presented in Table II. We limit the sample to firms with 250 to 750 employees in Columns 1-3 and those with 300 to 700 employees in Columns 4-5, and we use different controls and weights across the specifications. We find that an increase of £1 in the carbon price induces a 6 to 8 percent increase in R&D expenditures, which represents increase of about £200k-300k. These estimates are within the confidence bounds of Calel (2020)'s results when examining the impact of the EU-ETS on regulated firms' total R&D spending. We convert our estimates of the price level effects into elasticities and also estimate the elasticity directly by using the inverse hyperbolic sine of carbon pricing rather than the price in levels (Column 5) and find that they range between about 0.4 and 0.7, which is also consistent with the literature.[20]

[TABLE II HERE]

6.2 Policy Interaction Effects

We now turn to our main results, starting with a graphical representation and then providing the findings from the full interacted model along with a discussion of the magnitudes of the estimates.

6.2.1 Graphical Exposition of Interaction Effects

Limiting the sample to firms with fewer than 700 employees and more than 300, we estimate the effect of carbon pricing separately for firms just below and above the tax credit generosity threshold. We include our baseline set of controls and fixed effects—firm, year, and industry fixed effects, industry-year linear trends, and the running variable—and cluster standard errors at the industry level.

Figures III and IV show the coefficients with their 90% confidence intervals. Starting with Figure III, we find that while the effect of carbon prices on R&D is positive and large (about 12%) for firms over the tax credit threshold receiving a much lower tax credit benefit, the effect is substantially dampened for firms under the threshold receiving much higher tax credits. The effect is about 4% for these firms—a reduction of 8 percentage points. These findings suggest that there is a substantial negative interaction effect between the two policies on R&D.

[FIGURE III HERE]

In Figure IV, we plot the effects on quality-adjusted clean patents in Panel A and quality-adjusted dirty patents in Panel B. The findings are striking. Carbon prices for those receiving lower tax credits appear to have a very small positive effect on clean patenting (although the effect is not statistically distinguishable from zero), there is again a significant negative interaction effect such that the effect of carbon pricing is much lower for firms receiving higher tax credits and regulated by the EU-ETS relative to those that receive lower tax credits. Note that these effects represent the impact for firms that are regulated by the EU-ETS relative to those that are not—the interaction—so the negative effect plotted here does not suggest that carbon pricing reduces clean patenting for these firms. Rather, this demonstrates that the effect of carbon pricing for regulated

[20] We use the mean value of the carbon price in our estimation sample when converting the elasticities.

firms relative to those that are not regulated is greatly dampened when firms receive more generous tax credits.

[FIGURE IV HERE]

6.2.2 Regression Results

The results from estimating the fully interacted model of Equation 1 are shown in Table III and are consistent with the graphical exposition. Starting first with the effects on R&D in Column 1, we find that a £1 increase in the carbon price enhances R&D expenditures by 9.9% for firms that are regulated by the EU-ETS relative to firms that are not regulated, but this effect is dampened by 4.2 percentage points for regulated firms just under the tax credit threshold relative to regulated firms just above it. This equates to a 42% reduction in the carbon price effect for regulated firms receiving more generous tax credits relative to regulated firms that receive less generous tax credits. At the same time, once summing the relevant coefficients to examine the effect, both sets have about the same effect on R&D relative to unregulated firms. These results begin to hint at a change in innovation activities for regulated firms below and above the threshold, but the null interaction effect relative to unregulated firms could be masking a change in the composition of innovative activities since R&D is total R&D rather than that which is specifically associated with clean or dirty innovation.

Turning to the patenting results, we can see that there are indeed different directional effects on clean and dirty innovation. A £1 increase in the carbon price increases low-carbon patenting by 0.9% for regulated firms over the tax credit threshold, and this is reduced substantially (by 3.3 percentage points). This is consistent with firms using the tech-neutral tax credit funding for other activities rather than putting it towards enhancing their low-carbon innovation activities. When summing the relevant coefficients, we find that the total effect of carbon pricing on clean patents for regulated firms relative to unregulated firms falls to 0.6% for firms under the tax credit threshold (relative to 0.9% for regulated firms above it).

On the contrary, a £1 increase in the carbon price reduces dirty technology patenting for regulated firms by 0.3% relative to unregulated firms, which is intuitive given the expected directional effect of carbon pricing. But when regulated firms receive more generous tax credits, their dirty technology patenting increases by 1.5 percentage points relative to regulated firms that do not receive more generous tax credits. This suggests again that firms use the tech-neutral R&D funding to support their status quo activities. At the same time, when summing the relevant coe cients, we can see that there is no statistically signi cant policy interaction e ect when considering the e ects relative to unregulated rms|the carbon pricing reduces dirty patenting by 0.3% for rms both above and below the tax credit threshold.

[TABLE III HERE]

6.2.3 Elasticities and Interpreting Magnitudes of E ects

The interaction e ects and e ects on patenting in general may seem small at rst glance, but they are induced by just an incremental change in the carbon price, and patenting is rare in general. We calculate the implied elasticities based on the average value of our outcome variables (their levels) and summarize the overall takeaways from our main results in Table IV.

[TABLE IV HERE]

If we were to assume a carbon price of £50 per ton of CO2, which is higher than it was throughout our sample period but much lower than the most recent estimates of the social cost of carbon,[21] and if we make the (albeit strong) assumption that the e ects can be extrapolated linearly and homogenously across regulated rms, the carbon price e ects before considering the interaction with R&D subsidies would imply that a £50 carbon price would generate about 44 to 61 additional low-carbon patents. This is also similar to the results in Calel (2020), which indicate that UK rms produced about 64 additional low-carbon patents between 2005 and 2012 due to the EU-ETS. To put these numbers into context, Dechezleprêtre et al. (2022) nd that £1 million in public expenditures via the UK's R&D tax credit scheme yield 1.12 additional patents. Creating 44 to 61 would patents would thus cost between £39 and £54 million as opposed to generating billions in revenue through the EU-ETS.

6.2.4 Heterogeneity in Clean Technologies

We also explore whether there is heterogeneity in the interaction e ects on low-carbon technologies, examining patents associated with climate change mitigation technologies for industrial processes and practices separately from those associated with clean energy technologies. One can imagine that innovating in the former might be a more common response to carbon pricing in the industrial

[21] Rennert et al. (2022) nd that it is currently about $185 per ton of CO2.

sector, so this allows us to ensure that the effects are not just driven by the fact that these firms wouldn't be investing in clean energy innovation in the first place. We find approximately the same effects for both types of clean patenting (see Table V).

[TABLE V HERE]

6.3 Falsification and Robustness Checks

We conduct a number of falsification and robustness checks to ensure that the results are not sensitive to our modelling choices or driven by idiosyncrasies in our data. First, we impose artificial cutoffs using levels of employment for which there is no difference in the R&D tax credit generosity and thus should not find any differences in patenting or the carbon price effect on patenting. The results for clean and dirty patenting are provided in Panels A and B of Appendix Table B.4, respectively, when using pseudo-thresholds of 700 employees (Column 1), 900 employees (Column 2), and 950 employees (Column 3). We find no effects at these cutoffs, as expected.

Next, to ensure that our results are not driven strictly by clean electricity firms (e.g., wind generators) and that relatively "dirty" industries are indeed innovating, we drop firms in the power sector and find no differences in the policy effects on R&D expenditures, clean patenting, or dirty patenting (Column 1 of Appendix Tables B.6, B.7, and B.8, respectively). We also find no differences when including quadratic forms of the running variable polynomials (Column 2 of the respective Appendix tables for R&D, clean patents, and dirty patents). Lastly, we drop industry fixed effects to see if the effects change when we also identify the effect of carbon pricing for unregulated firms. This allows us to explore whether firms in unregulated industries are a reasonable control group—they could be indirectly affected by carbon prices, but if so, our results might be biased. We find that there is no effect of carbon pricing on these firms and the main effects also do not change (Column 3 in the respective Appendix tables for R&D, clean patents, and dirty patents).

6.4 No Exit or Input Reallocation

Although innovation can be good for growth, environmental regulations and policies also could also be costly due to reallocation, as it can leave some workers without jobs. For example, Walker (2013) found that there were significant reallocative costs due to non-employment and lower future earnings for workers who had been in industries that became regulated following implementation of the 1990 Clean Air Act. We explore whether this is the case in our setting by estimating the policy effects on firm exit and labor, and do not find effects of carbon pricing nor tax credits (see Columns 1 and 2 of Table VI.

Furthermore, although we find that firms do indeed innovate in response to carbon pricing, another potential approach to complying is installing pollution abatement equipment. This could, of course, have positive implications for firms' environmental footprint, but it is less likely to enable longer term growth since it just entails an end-of-pipe capital investment rather than a change in the way in which a firm operates or the development of a new technology, nor would it create the positive knowledge spillovers that could induce other firms to innovate. We find there to be no effect of either policy on capital (Column 3 of Table VI), and when breaking down capital into the type of capital, we also do not find effects on or plant and vehicle investments specifically (Column 4 of Table VI). While it could be that a null effect occurs because old equipment is displaced with new, we also would expect there to be some effect on labor or the capital-labor ratio if that was the case, since end-of-pipe abatement equipment (like scrubbers) often require additional workers. As noted earlier, we find no effects on labor, and we also find no effect on the capital-labor ratio (Column 5 of Table VI.

[TABLE VI HERE]

7 Path Dependence as the Underlying Mechanism

We now turn to exploring whether path dependence can explain our findings. Technological progress is an endogenous process whereby a firm's own knowledge endowments affect their technological choices as well as technology performance, which tends to be a function of market-level knowledge endowments (i.e., the technology's maturity). As such, even though tech-neutral R&D subsidies do not formally favor specific technologies, they may inherently favor incumbent technologies and industries.

We construct firm-level knowledge endowments as firms' cumulative patenting activity in clean and dirty technologies and market-level knowledge endowments by cumulative patents within-industry at the 2-digit SIC level, and we estimate whether such measures impact firm patenting behavior directly as well as whether it adjusts the marginal effect of carbon pricing and the policy interaction effects.

Table VII and Table VIII provide the findings for the effects on clean and dirty patenting, respectively. Column 1 of each table presents the baseline results for comparison. In Column 2, we include cumulative patenting in clean or dirty innovation, and find positive relationships between knowledge endowments and flow of patents for the respective type of innovation (i.e., clean and dirty). The point of departure begins once we interact them with the policy instruments. In Column 3 of Table VII, we find that having larger knowledge endowments of clean patents increases the carbon price effect on clean patenting by 1.1 percentage points, and R&D tax credits once again reduce this effect. On the other hand, no such interactions exist for dirty innovation (Column 3 of Table VIII), which is expected since carbon pricing does not enhance such innovation in the first place. Intra-firm path dependence thus appears to not just directly affect the direction of innovation but also through the carbon pricing and its interaction with R&D subsidies.

Lastly, we examine whether market-level cumulative knowledge stocks impact the direction of innovation. We estimate their effects on clean and dirty patent flows in Column 5 of their respective tables, and find that they have no direct effect or indirect effect through the policy instruments. These findings suggest that firms' technology choices depend on the historical evolution of their own innovation pursuits and within-firm pivoting as firms displace dirty innovation pursuits with those that are clean as opposed to simply increasing clean innovation efforts without reducing dirty innovation.

[TABLE VII HERE]

[TABLE VIII HERE]

8 Conclusion

Technology-neutrality has long-been touted as a staple of designing policy and regulation. Economic theory indeed suggests that efficient government intervention should entail identifying and addressing a market failure but without specifying the technology or approach for doing so, as "picking winners" can stifle entry and competition. At the same time, technological progress is an endogenous process through which firms make decisions about their innovation pursuits based on their knowledge endowments and technology performance. This raises questions about whether tech-neutral innovation policy is truly tech-neutral, as technological progress itself is not tech-neutral. It inherently favors incumbent and more mature technologies. Furthermore, not all innovations are created equally, and as some can improve social welfare by more than others, policymakers may wish to not just increase the overall level of innovation across the economy but also steer its direction.

In this paper, we posit and show that tech-neutral R&D subsidies actually can impact the composition of innovation and have unintended consequences for the direction of innovation. This is due to the path dependent nature of technological progress. That is, innovations that could address society's most pressing challenges tend to be characterized by a \double-externality" challenge, whereby the incentive to innovate is affected not just by imperfect appropriability but also consumption or production externalities. The existence of two market failures justifies two interventions, and theory suggests that both should remain agnostic regarding the specific solutions.

But because technological choice is determined by a firm's knowledge endowments and technology performance, which in turn tends to be a function of technology maturity, tech-neutral policy may inherently favor the incumbent technology or industry. This is indeed what we find in the context of low-carbon energy and climate change mitigation innovation. Carbon pricing enhances innovation in such technologies, and while R&D tax credits could theoretically serve as complementary policy instruments to further enhance such efforts, we find that they instead undermine the directional effect of carbon pricing on innovation when they are entirely tech-neutral because firms can also use the funding to support their status quo activities. This is a within-firm phenomenon|clean innovation does not just increase in response to carbon pricing while dirty innovation remains flat, but rather firms pivot in their innovation activities such that low-carbon patenting displaces dirty technology patenting. Policymakers and economists may therefore wish to reconsider the degree to which innovation policy should remain tech-neutral when the objective is not just to increase the overall level of innovation but to also steer its direction, especially when such innovative activity is characterized by multiple market failures.

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MAIN TEXT TABLES

Table I: Summary Statistics for Baseline Sample

	Observations	Mean	St. Dev.
Panel A: R&D Expenditures and Firm Characteristics			
R&D Expenditures (000s GBP)	1,254	3006.59	15147
R&D as Percent of Revenue	1,253	3.046	13.688
Capital-Labor Ratio (log)	4,075	3.473	1.307
Age	4,211	35.174	29.203
Revenue (000s GBP) (log)	4,142	11.088	1.032
Total Assets (000s GBP) (log)	4,209	10.919	1.285
Panel B: Granted Patent Families by Tech Type			
Any technology	4,211	0.290	1.682
Clean Manu. + Energy Techs	4,211	0.012	0.167
Dirty Manu. + Energy Techs	4,211	0.010	0.157

Notes: Summary statistics for R&D expenditures, rm characteristics, and patenting activity for rms in our sample with 200 to 800 employees in the post-policy period (2010-2019).

Table II: E ect of Carbon Price on R&D Expenditures on Its Own

	(1)	(2)	(3)	(4)	(5)
CP	0.061***	0.058***	0.067***	0.084***	
	(0.011)	(0.010)	(0.010)	(0.010)	
ihs(CP)					0.714***
					(0.090)
Observations	906	906	906	679	679
Sample Mean R&D	3349	3349	3349	3320	3320
Elasticity	0.403	0.383	0.442	0.561	0.714
Sample Window:					
250 to 750 Employees	x	x	x		
300 to 700 Employees				x	x
Running Variable Controls		x	x	x	x
Uniform Weights	x	x			
Triangular weights			x	x	x

Notes: Table presents the e ects of carbon prices on (log) R&D expenditures in the post-policy period (2010-2019) for EU-ETS regulated rms before accounting for policy interactions. All speci cations include rm, year, and industry xed e ects as well as industry-year linear trends. Standard errors are clustered at the industry level. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table III: Main Results
Carbon Price and R&D Tax Credit Interactions|E ects on R&D and Patenting

	log(R&D)	ihs(Clean Patents)	ihs(Dirty Patents)
	(1)	(2)	(3)
CP * Reg'd	0.099***	0.009**	-0.003***
	(0.007)	(0.003)	(0.001)
CP * Reg'd * TC	-0.042*	-0.033***	0.015***
	(0.022)	(0.009)	(0.003)
TC * Reg'd	0.064	0.192**	-0.015
	(0.290)	(0.072)	(0.023)
CP * TC	0.041***	0.030***	-0.015***
	(0.009)	(0.009)	(0.003)
TC	0.050	-0.200**	0.016
	(0.058)	(0.075)	(0.022)
Observations	679	2061	2061
Mean Dep. Var. (Levels)	3,320	0.303	0.052
Firm FEs	x	x	x
Year FEs	x	x	x
Industry FEs	x	x	x
Industry-year trends	x	x	x

Notes: Table presents the main results of the paper|the policy interaction e ects on R&D expenditures and patenting in low-carbon and dirty technologies. The dependent variable is log(R&D) in Column 1. In Columns 3 and 4, the dependent variable is the inverse hyperbolic sine of clean and dirty patents, respectively. Firms with 300 to 700 employees are included in all cases, and we use triangular weights. Each speci cation also included rst-order polynomials of the (centered) running variable that di er on each side of the tax credit threshold. Standard errors are clustered by industry. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table IV: Summary of Carbon Price E ects & Magnitudes

Dep. Var.:	log(R&D)	ihs(Clean Patents)	ihs(Dirty Patents)
	(1)	(2)	(3)
Carbon Price E ects on Regulated Firms			
w/Higher TCs Relative to Reg'd w/Lower TCs	-0.042	-0.033	0.015
w/Lower TCs Relative to Unreg'd Firms	0.099	0.009	-0.003
w/Higher TCs Relative to Unreg'd Firms	0.098	0.006	0.000
Mean of Dep. Var. (Levels)	3,320	0.303	0.052
Elasticity (Relative to Unregulated)			
Reg'd Firms w/Lower TCs	0.653	0.059	-0.020
Reg'd Firms w/Higher TCs	0.647	0.040	-0.020
CP E ect Di erence at TC Threshold (Relative to Unregulated)	-1%	-33%	0

Notes: Table provides the carbon price e ects and magnitudes based on tax credit level eligibility.

Table V: Production and Processing vs. Clean Tech and Energy Management

Dep. Var. (ihs)	Production and Processing Patents (1)	Clean Tech and Management Patents (2)
CP * Reg'd	0.006***	0.007**
	(0.002)	(0.003)
CP * Reg'd * TC	-0.026***	-0.027***
	(0.007)	(0.008)
TC * Reg'd	0.093*	0.175**
	(0.049)	(0.066)
CP * TC	0.023***	0.026***
	(0.007)	(0.008)
TC	-0.108*	-0.176**
	(0.055)	(0.069)
Observations	2061	2061
Mean Dep. Var.	0.02	0.01
Firm FEs	x	x
Year FEs	x	x
Industry FEs	x	x
Industry-year trends	x	x

Notes: Table presents heterogeneous interaction e ects on climate change mitigation inventions as measured by (ihs) quality-adjusted patents. Column 1 estimates the e ects on patents related to the production or processing of goods and Column 2 estimates the e ects on patents related to clean energy and energy management with climate change mitigation potential. We use triangular weights and include rst-order polynomials of the (centered) running variable that di er on each side of the tax credit threshold in all speci cations. Firms with 300 to 700 employees are included in the sample. Standard errors are clustered by industry. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table VI: No Policy E ects on Exit or Inputs

Dep. Var.:	Exit	log(L)	log(K)	log(PlantVeh)	log(K/L)
	(1)	(2)	(3)	(4)	(5)
CP * Reg'd	-0.000	0.041	0.028	0.019	-0.018
	(0.001)	(0.041)	(0.025)	(0.013)	(0.018)
CP * Reg'd * TC	-0.001	-0.033	-0.045	-0.021	-0.004
	(0.001)	(0.039)	(0.029)	(0.021)	(0.016)
TC * Reg'd	0.014	0.048	0.170	-0.099	0.058
	(0.015)	(0.297)	(0.237)	(0.178)	(0.129)
CP * TC	0.000	0.035	0.041	0.015	0.003
	(0.000)	(0.039)	(0.029)	(0.019)	(0.015)
TC	-0.002	-0.076	-0.174	0.182	-0.086
	(0.003)	(0.293)	(0.230)	(0.166)	(0.125)
Observations	2061	2047	1998	1833	1997
Mean Dep. Var.	0.00	6.09	9.77	9.05	3.66

Notes: Table presents the e ects on exit (Column 1), labor (Column 2), capital (Column 3), plant and vehicle-speci c capital (Column 4), and the capital-labor ratio (Column 5) (all in logs). All speci cations include rm, year, and industry xed e ects as well as industry-year linear trends. Standard errors are clustered at the industry level. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table VII: Own Knowledge Endowments and Path Dependence in Clean Patenting

Dep. Var.: ihs(clean patents)	(1)	(2)	(3)	(4)	(5)
CP * Reg'd	0.009**	0.011***	0.007*	0.002	0.010*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
CP * Reg'd * TC	-0.033***	-0.042***	-0.037***	-0.031***	-0.028***
	(0.009)	(0.012)	(0.011)	(0.008)	(0.010)
TC * Reg'd	0.192**	0.262***	0.231**	0.154*	0.192**
	(0.072)	(0.089)	(0.087)	(0.081)	(0.076)
CP * TC	0.030***	0.038***	0.036***	0.033***	0.030***
	(0.009)	(0.010)	(0.010)	(0.008)	(0.009)
TC	-0.200**	-0.262**	-0.252**	-0.188**	-0.202**
	(0.075)	(0.098)	(0.097)	(0.081)	(0.079)
Own Clean Stock		0.513***	0.426***		
		(0.154)	(0.103)		
OwnClean * CP * Reg'd			0.011**		
			(0.004)		
OwnClean * CP * Reg'd * TC			-0.014***		
			(0.003)		
Own Dirty Stock				0.113	
				(0.088)	
OwnDirty * CP * Reg'd				0.016**	
				(0.007)	
OwnDirty * CP * Reg'd * TC				-0.013***	
				(0.005)	
Mrkt Clean Stock					-0.001
					(0.017)
MrktClean * CP * Reg'd					-0.000
					(0.000)
MrktClean * CP * Reg'd * TC					-0.001
					(0.001)
Observations	2061	2051	2051	2051	2051
Mean Dep. Var.	0.02	0.02	0.02	0.02	0.02

Notes: All speci cations include rm, year, and industry xed e ects as well as industry-year linear trends. Standard errors are clustered at the industry level. Asterisks denote * p < 0.10, ** p < 0.05, *** p < 0.01.

Table VIII: Own Knowledge Endowments and Path Dependence in Dirty Patenting

Dep. Var.: ihs(dirty patents)	(1)	(2)	(3)	(4)	(5)
CP * Reg'd	-0.003***	-0.009***	-0.009***	-0.004**	-0.006
	(0.001)	(0.003)	(0.003)	(0.002)	(0.005)
CP * Reg'd * TC	0.015***	0.008***	0.008***	0.014***	0.015***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
TC * Reg'd	-0.015	-0.059***	-0.059***	-0.021	-0.016
	(0.023)	(0.017)	(0.020)	(0.026)	(0.025)
CP * TC	-0.015***	-0.006**	-0.007***	-0.014***	-0.015***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
TC	0.016	0.052***	0.050**	0.012	0.016
	(0.022)	(0.017)	(0.021)	(0.022)	(0.024)
Own Dirty Stock		0.351***	0.331***		
		(0.060)	(0.033)		
OwnDirty * CP * Reg'd			0.001		
			(0.005)		
OwnDirty * CP * Reg'd * TC			0.005		
			(0.010)		
Own Clean Stock				0.052	
				(0.049)	
OwnClean * CP * Reg'd				0.006**	
				(0.002)	
OwnClean * CP * Reg'd * TC				0.016*	
				(0.009)	
Mrkt Dirty Stock					-0.008
					(0.015)
Mrkt Dirty Stock					0.000
					(0.001)
MrktDirty * CP * Reg'd * TC					0.000
					(0.000)
Observations	2061	2051	2051	2051	2051
Mean Dep. Var.	0.01	0.01	0.01	0.01	0.01

Notes: All speci cations include rm, year, and industry xed e ects as well as industry-year linear trends. Standard errors are clustered at the industry level. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table IX: Heterogeneity in Patenting by Pre-Policy Average Wages

	Clean Patenting		Dirty Patenting	
	High Wages	Low Wages	High Wages	Low Wages
	(1)	(2)	(3)	(4)
CP * Reg'd	0.011**	-0.004	-0.005**	-0.000
	(0.005)	(0.007)	(0.002)	(0.000)
CP * Reg'd * TC	-0.048***	-0.008	0.020***	0.001
	(0.012)	(0.015)	(0.004)	(0.001)
CP * TC	0.042***	0.006	-0.021***	-0.000
	(0.011)	(0.015)	(0.003)	(0.000)
TC * Reg'd	0.321***	0.029	-0.019	-0.008
	(0.099)	(0.058)	(0.029)	(0.006)
TC	-0.341***	-0.026	0.034	0.004
	(0.104)	(0.057)	(0.029)	(0.003)
Observations	1052	1009	1052	1009
Mean Dep. Var.	0.03	0.02	0.03	0.00

Notes: Table presents ndings from estimating e ects separately for rms with pre-policy average wages that are below and above the estimating sample's median. All speci cations include rm, year, and industry xed e ects as well as industry-year linear trends. Standard errors are clustered at the industry level. Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

MAIN TEXT FIGURES

Figure I: EU-ETS Carbon Prices (2005-2019)

Note: EU-ETS carbon prices as measured by the annual average of daily one-month ahead futures prices.

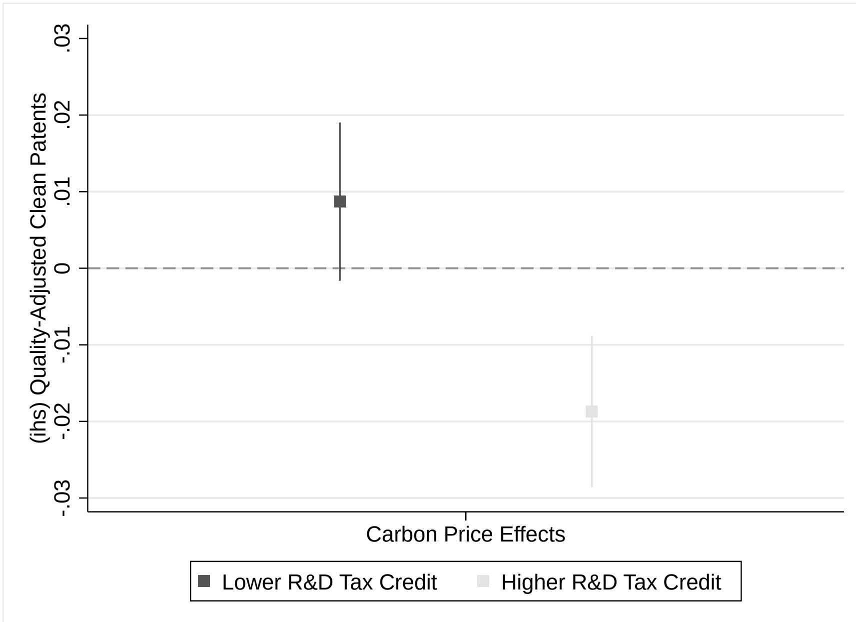
Figure II: E ect of Tax Credit Only on R&D Expenditures

Note: Figure plots average R&D expenditures for bins of observations along the rm size distribution with a second-order polynomial t. Includes rms with 200 to 800 employees in post-policy years.

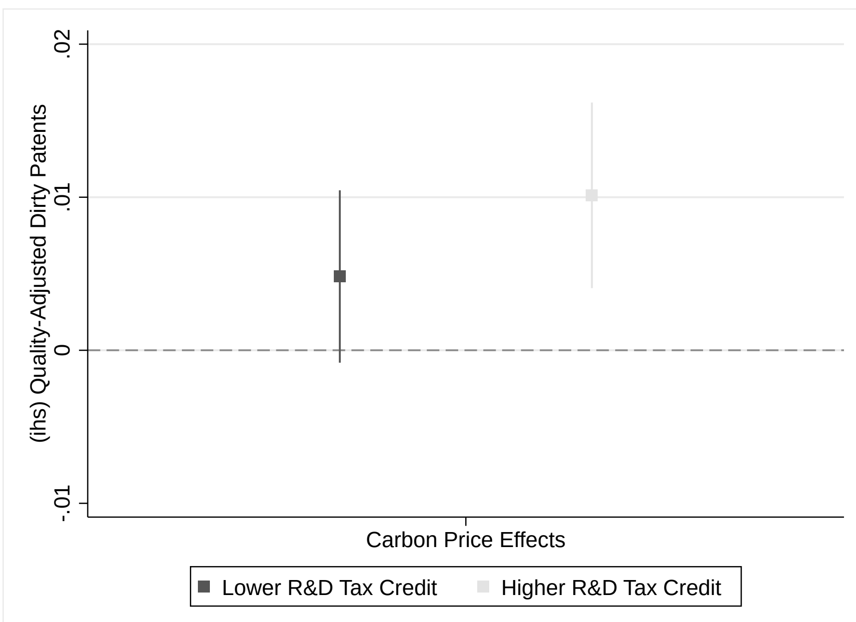
Figure III: Carbon Price E ects on R&D Expenditures for Firms Eligible for High vs. Low Tax Credits

Note: Figure plots coe cients for estimates of carbon price e ects on R&D expenditures for rms just over the tax credit generosity threshold (lower tax credit) and just under it (higher tax credit) with 90% con dence intervals. The di erence in the e ects re ects the carbon pricing and tax credit interaction e ect.

Figure IV: Carbon Price E ects on Clean and Dirty Patenting for Firms Eligible for High vs. Low Tax Credits



(a) Quality-Adjusted Clean Patents



(b) Quality-Adjusted Dirty Patents

Note: Figure plots coefficients for estimates of carbon price effects on clean and dirty quality-adjusted patents for firms just over the tax credit generosity threshold (lower tax credit) and just under it (higher tax credit) with 90% confidence intervals. The difference in the effects reflects the carbon pricing and tax credit interaction effect.

A Appendix: Additional Data Preparation Details | Online Only

Forthcoming.

B Appendix: Additional Tables | Online Only

Table B.1: R&D Tax Credit Rates for Small and Medium-Sized Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Enhancement Rate	Payable Credit	Low Corp. Tax	Main Corp. Tax	Profit-Making % Benefit		Loss-Making % Benefit
					Low Tax	Main Tax	No Tax
2008	0.75	0.14	0.21	0.28	0.16	0.21	0.105
2009	0.75	0.14	0.21	0.28	0.16	0.21	0.105
2010	0.75	0.14	0.21	0.28	0.16	0.21	0.105
2011	1.00	0.125	0.20	0.26	0.20	0.26	0.125
2012	1.25	0.11	0.20	0.24	0.25	0.30	0.138
2013	1.25	0.11	0.20	0.23	0.25	0.29	0.138
2014	1.25	0.145	0.20	0.21	0.25	0.26	0.181
2015	1.30	0.145	0.20	0.20	0.26	0.26	0.189
2016	1.30	0.145	0.20	0.20	0.26	0.26	0.189
2017	1.30	0.145	0.19	0.19	0.25	0.25	0.189

Notes: Table provides R&D enhancement rates for firms defined as small and medium-sized firms according to the R&D tax credit scheme as well as corporate tax rates (Columns 1-4), which determine the R&D benefits (Columns 5-7). The R&D benefit is determined by whether the firm is loss-making and thus qualifies for the payable credit or profit-making and thus qualifies for the tax credit. For profit-making firms, the benefit depends on whether they make less than 300k in profits or more than 300k in profits, whereby they face the low corporate tax rate in the former case and the main tax rate in the latter case. The percent benefits of the tax credits is calculated as the product of the enhancement rate and corporate tax rate for profit-making firms and the enhancement rate times the payable credit for loss-making firms.

Table B.2: Covariate Balance in R&D Tax Credit Pre-Policy Years

Dep. var.	log(Revenue) (1)	log(Capital) (2)	log(Avg. Wages) (3)	Pr(Oper. Cash>0) (4)	Pr(Profits>0) (5)
Treated (TC)	0.012	0.055	0.009	0.027	-0.025
	(0.043)	(0.039)	(0.012)	(0.045)	(0.033)
Observations	3,138	3,166	3,051	978	3,216
Firm fixed effects	x	x	x	x	x
Industry-year fixed effects	x	x	x	x	x

Notes: Regression discontinuity results demonstrating covariate balance around the tax credit threshold in pre-policy years. Firms with 200 to 800 employees are included. First order polynomials of the (centered) running variable are included separately for each side of the threshold and standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.3: Effect of R&D Tax Credit Only on R&D Expenditures

Dep. Var. (log):	R&D (1)	R&D (2)	R&D (3)	R&D (4)
Treated (TC)	0.245	0.394**	0.409*	0.467*
	(0.163)	(0.182)	(0.211)	(0.249)
Observations	2,086	1,953	1,412	1,092
Firm FEs	x	x	x	x
Year FEs	x	x	x	x
Industry-Year FEs			x	x
100 to 900 Employees	x	x		
150 to 850 Employees			x	
200 to 800 Employees				x

Notes: Effect of R&D tax credit on (log) R&D expenditures in the post-policy period. All specifications include first-order polynomials of the (centered) running variable that vary on each side of the threshold. Standard errors are clustered at the industry level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.4: Pseudo-Threshold Falsi cation Tests

Pseudo-Threshold:	700 Employees (1)	900 Employees (2)	950 Employees (3)
Panel A: E ects on ihs(Clean Patents)			
CP * Reg'd	0.005	-0.003	-0.001
	(0.006)	(0.002)	(0.001)
CP * Reg'd * Pseudo	-0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)
Pseudo * Reg'd	0.030	-0.025	-0.019
	(0.023)	(0.016)	(0.020)
CP * Pseudo	0.005	-0.001	-0.001
	(0.003)	(0.002)	(0.001)
Pseudo	-0.057*	-0.001	0.001
	(0.029)	(0.010)	(0.006)
Observations	1028	526	468
Mean Dep. Var.	0.02	0.00	0.00
Panel B: E ects on ihs(Dirty Patents)			
CP * Reg'd	-0.002	-0.007	-0.000
	(0.005)	(0.014)	(0.016)
CP * Reg'd * Pseudo	0.002	0.008	0.012
	(0.004)	(0.016)	(0.022)
Pseudo * Reg'd	-0.010	-0.051	-0.022
	(0.029)	(0.098)	(0.121)
CP * Pseudo	0.002*	-0.003	-0.001
	(0.001)	(0.015)	(0.019)
Pseudo	-0.023	-0.013	-0.093*
	(0.014)	(0.068)	(0.051)
Observations	1028	526	468
Mean Dep. Var.	0.01	0.02	0.02

Notes: Effect of R&D tax credit on (log) R&D expenditures in the post-policy period. All specifications include first-order polynomials of the (centered) running variable that vary on each side of the threshold. Standard errors are clustered at the industry level. Asterisks denote $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.5: Alternative Approaches to Measuring Patenting

	Patent Flows			Pr[Flow>0]	
	Clean	Dirty	All Other	Clean	Dirty
	(1)	(2)	(3)	(4)	(5)
CP * Reg'd	0.003**	-0.002**	-0.002	0.003**	-0.002**
	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)
CP * Reg'd * TC	-0.017***	0.006**	-0.009	-0.015***	0.009***
	(0.004)	(0.002)	(0.013)	(0.004)	(0.003)
TC * Reg'd	0.083***	-0.071***	-0.209	0.077**	-0.086***
	(0.028)	(0.024)	(0.125)	(0.034)	(0.029)
CP * TC	0.016***	-0.006**	0.011	0.013***	-0.008**
	(0.004)	(0.002)	(0.012)	(0.004)	(0.003)
TC	-0.086***	0.069***	0.121	-0.074**	0.082***
	(0.029)	(0.023)	(0.119)	(0.033)	(0.029)
Observations	2061	2061	2051	2061	2061
Mean Dep. Var.	0.01	0.01	0.15	0.01	0.01

Notes: Table presents results from when using alternative measures of patenting as outcomes. In Columns 1 and 2, we use patent flows before adjusting for quality. In Columns 3 and 4, we use an indicator equal to one if the patent flow is greater than 0. In Column 5, we use the flow of patents in all other technologies not captured in the clean or dirty categories. All specifications include firm, year, and industry fixed effects as well as industry-year linear trends as well as the (centered) running variable. Standard errors are clustered at the industry level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.6: Additional Robustness Checks for E ects on R&D

	Drop Power Sector (1)	Quadratic Poly. (2)	Drop Industry FEs (3)
CP * Reg'd	0.096***	0.105***	0.099***
	(0.007)	(0.011)	(0.007)
CP * Reg'd * TC	-0.042*	-0.048	-0.042*
	(0.022)	(0.030)	(0.022)
TC * Reg'd	0.072	0.127	0.064
	(0.289)	(0.324)	(0.290)
CP * TC	0.041***	0.047***	0.041***
	(0.009)	(0.013)	(0.009)
TC	0.045	-0.056	0.050
	(0.057)	(0.119)	(0.058)
CP			-0.013
			(16.011)
Observations	666	679	679
Mean Dep. Var.	6.70	6.69	6.69

Notes: Interaction effects on (log) R&D expenditures. Firms with 300 to 700 employees are included in all columns. First-order polynomials of the (centered) running variable that vary on each side of the threshold included in Columns 1 and 3 and second-order polynomials in Column 2. In Column 1, we drop the power sector. In Column 3, we drop industry FEs. Standard errors are clustered at the industry level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.7: Additional Robustness Checks for Effects on Clean Patenting

	Drop Power Sector (1)	Quadratic Poly. (2)	Drop Industry FEs (3)
CP * Reg'd	0.009**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)
CP * Reg'd * TC	-0.034***	-0.031***	-0.031***
	(0.009)	(0.009)	(0.009)
TC * Reg'd	0.191**	0.184**	0.182**
	(0.072)	(0.073)	(0.073)
CP * TC	0.030***	0.030***	0.030***
	(0.009)	(0.009)	(0.009)
TC	-0.201**	-0.199**	-0.192**
	(0.076)	(0.078)	(0.078)
CP			-0.070
			(1.587)
Observations	1924	2061	2061
Mean Dep. Var.	0.02	0.01	0.01

Notes: Interaction effects on (ihs) quality-adjusted clean patents. Firms with 300 to 700 employees are included in all columns. First-order polynomials of the (centered) running variable that vary on each side of the threshold included in Columns 1 and 3 and second-order polynomials in Column 2. In Column 1, we drop the power sector. In Column 3, we drop industry FEs. Standard errors are clustered at the industry level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table B.8: Additional Robustness Checks for Effects on Dirty Patenting

	Drop Power Sector (1)	Quadratic Poly. (2)	Drop Industry FEs (3)
CP * Reg'd	-0.003***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)
CP * Reg'd * TC	0.015***	0.016***	0.015***
	(0.003)	(0.003)	(0.003)
TC * Reg'd	-0.014	-0.021	-0.015
	(0.024)	(0.022)	(0.023)
CP * TC	-0.015***	-0.016***	-0.015***
	(0.003)	(0.003)	(0.003)
TC	0.015	-0.001	0.016
	(0.023)	(0.019)	(0.022)
CP			-0.001
			(1.366)
Observations	1924	2061	2061
Mean Dep. Var.	0.02	0.01	0.01

Notes: Interaction effects on (ihs) quality-adjusted dirty patents. Firms with 300 to 700 employees are included in all columns. First-order polynomials of the (centered) running variable that vary on each side of the threshold included in Columns 1 and 3 and second-order polynomials in Column 2. In Column 1, we drop the power sector. In Column 3, we drop industry FEs. Standard errors are clustered at the industry level. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

C Appendix: Additional Figures | Online Only

Figure C.1: Examples of Patent Classi cations for Technologies with Climate Change Mitigation Potential in the Industrial Sector

Y02P	**CLIMATE CHANGE MITIGATION TECHNOLOGIES IN THE PRODUCTION OR PROCESSING OF GOODS** [2015-11]
	NOTE This subclass covers climate change mitigation technologies in any kind of industrial processing or production activity, including the agroalimentary industry, agriculture, fishing, ranching and the like.
- **Y02P 10/00**	**Technologies related to metal processing** [2015-11]
- Y02P 10/10	. Reduction of greenhouse gas [GHG] emissions [2015-11]
Y02P 10/122	. . by capturing or storing CO_2 [2020-08]
Y02P 10/134	. . by avoiding CO_2, e.g. using hydrogen [2020-08]
Y02P 10/143	. . of methane [CH_4] [2020-08]
Y02P 10/146	. . Perfluorocarbons [PFC]; Hydrofluorocarbons [HFC]; Sulfur hexafluoride [SF_6] [2020-08]
Y02P 10/20	. Recycling [2020-08]
Y02P 10/25	. Process efficiency [2020-08]
Y02P 10/32	. using renewable energy sources [2020-08]
- **Y02P 20/00**	**Technologies relating to chemical industry** [2015-11]
- Y02P 20/10	. Process efficiency [2020-08]
Y02P 20/129	. . Energy recovery, e.g. by cogeneration, H_2recovery or pressure recovery turbines [2020-08]
Y02P 20/133	. . Renewable energy sources, e.g. sunlight [2020-08]
- Y02P 20/141	. Feedstock [2020-08]
Y02P 20/143	. . the feedstock being recycled material, e.g. plastics [2020-08]
Y02P 20/145	. . the feedstock being materials of biological origin [2020-08]
- Y02P 20/151	. Reduction of greenhouse gas [GHG] emissions, e.g. CO_2 [2020-08]
Y02P 20/155	. . Perfluorocarbons [PFC]; Hydrofluorocarbons [HFC]; Hydrochlorofluorocarbons [HCFC]; Chlorofluorocarbons [CFC] [2020-08]

Figure C.2: Examples of Patent Classi cations for Clean Energy Technologies

Y02B 10/00	**Integration of renewable energy sources in buildings**
Y02B 10/10	. Photovoltaic [PV]
Y02B 10/20	. Solar thermal
Y02B 10/30	. Wind power
Y02B 10/40	. Geothermal heat-pumps
Y02B 10/50	. Hydropower in dwellings
Y02B 10/70	. Hybrid systems, e.g. uninterruptible or back-up power supplies integrating renewable energies
Y02B 20/00	**Energy efficient lighting technologies, e.g. halogen lamps or gas discharge lamps**
Y02B 20/30	. Semiconductor lamps, e.g. solid state lamps [SSL] light emitting diodes [LED] or organic LED [OLED]
Y02B 20/40	. Control techniques providing energy savings, e.g. smart controller or presence detection
Y02B 20/72	. in street lighting

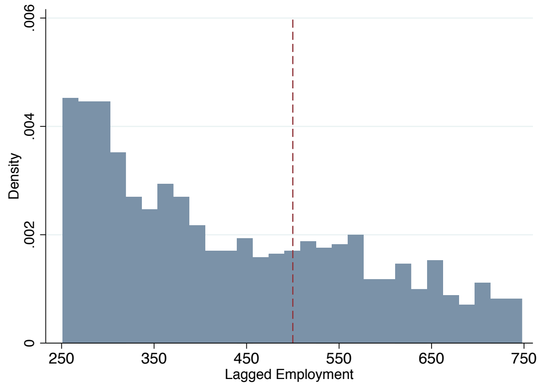
Figure C.3: Examples of Patent Classi cations for Dirty Industrial Sector Technologies

F23	**COMBUSTION APPARATUS; COMBUSTION PROCESSES** [2013-01]
F23C	**METHODS OR APPARATUS FOR COMBUSTION USING FLUID FUEL OR SOLID FUEL SUSPENDED IN {A CARRIER GAS OR} AIR** (burners F23D) [2019-08]
F23K	**FEEDING FUEL TO COMBUSTION APPARATUS** (fuel feeders specially adapted for fluidised bed combustion apparatus F23C 10/22) [2020-01]
F23B 30/00	**Combustion apparatus with driven means for agitating the burning fuel; Combustion apparatus with driven means for advancing the burning fuel through the combustion chamber** [2013-01]
F23B 30/02	. with movable, e.g. vibratable, fuel-supporting surfaces; with fuel-supporting surfaces that have movable parts [2013-01]
F23B 30/04	. . with fuel-supporting surfaces that are rotatable around a horizontal or inclined axis and support the fuel on their inside, e.g. cylindrical grates [2013-01]

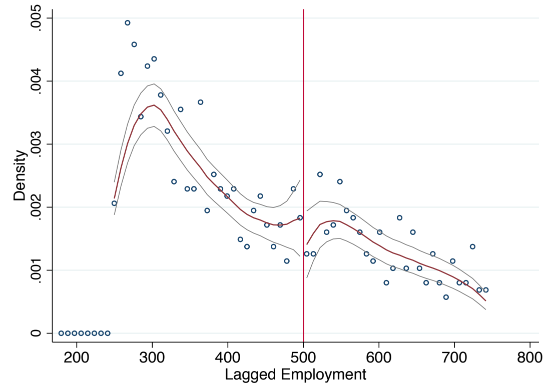
Figure C.4: Examples of Patent Classi cations for Dirty Energy Technologies

E21B	**EARTH DRILLING, e.g. DEEP DRILLING** (mining, quarrying E21C; making shafts, driving galleries or tunnels E21D); **OBTAINING OIL, GAS, WATER, SOLUBLE OR MELTABLE MATERIALS OR A SLURRY OF MINERALS FROM WELLS**
E21B 43/00	**Methods or apparatus for obtaining oil, gas, water, soluble or meltable materials or a slurry of minerals from wells** (applicable only to water E03B; obtaining oil-bearing deposits or soluble or meltable materials by mining techniques E21C 41/00; pumps F04) [2020-05]

Figure C.5: No Evidence of Bunching at Tax Credit Threshold | All Years (2010-2019)



(a) Histogram Based Upon Employment



(b) McCrary Density Test Based Upon Employment

Note: Histogram and McCrary test for discontinuity in distribution density of total employment at the tax credit generosity threshold. Sample includes firms reporting R&D expenditures with 250 to 750 employees. Log difference in density height of -0.350 with a standard error of 0.300.