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# Innovation and Emissions in Europe

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**Abstract**

Innovation is widely believed to play an important role in addressing climate change. Nevertheless, estimating such effects is difficult due to the endogeneity of innovation measures. I use a novel shift-share instrument building from cross-border patent citations to deal with this endogeneity. Using data for 27 European countries across 20 manufacturing industries from 1995-2019, I find evidence of significant endogeneity bias that overstates the causal effect of patents on emissions. Further, if anything, it seems that new non-green patents may increase emissions. This then suggests that relying on new technologies alone to solve the climate crisis is potentially ineffective.

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# 1 Introduction

"*If we're going to get to zero carbon emissions overall, we have a lot of inventing to do.*"

– Bill Gates 2019

Climate change is undoubtedly one of the major threats facing global stability. As weather patterns shift rapidly, there is widespread expectation that this will have major economic, political, social, and biological consequences. As the above quote illustrates, technological innovation is expected to play a major role in both reducing pollution and dealing with the changes wrought by climate change, particularly in light of the limited behavioural responses found in society as a whole. This naturally begs the question of what impact innovation, often measured as patents, has on pollution levels. Although there is a sincere hope that more innovation leads to lower emissions, this is not the only potential relationship. For example, when innovation leads to new technologies – e.g. internal combustion engines or artificial intelligence – this can increase emissions. Thus, the precise relationship requires careful econometric analysis.

A major difficulty in that task is that patents may well be endogenous in the estimation. This can arise if, for example, higher emissions prompt governments to respond by implementing policies which themselves drive innovation. Alternatively, firms may alter their patenting behaviour in response to emissions. For example, if high emissions leads to consumer demand for "green" products, firms may respond by generating green patents which provide those new products. Even more concerning is that those green patents may simply pay lip service to environmental outcomes and act as a "greenwashing" marketing ploy rather than a sincere effort to curb emissions. Thus, to estimate the underlying relationship, it is important to tackle the endogeneity of patents head on. This paper does so using a novel approach based off of patent citations that constructs a shift-share instrument as per Bartik (1991).

I do so by combining data on emissions of greenhouse gases, carbon dioxide, and suspended particulates for 27 European across 20 manufacturing industries from 1995-2019 with patent data. In particular, using the technology codes for individual patents I construct the stock of green and brown patent applications – i.e. those that address climate and energy use versus those that do not – across countries and industries. In addition, I use backward citation data from 1980-1990 to construct exposure of a given country-industry's patents to those elsewhere. When combined with the patent stock in other countries, this allows me to create green and brown instruments that vary by country-industry-year.

When ignoring the potential endogeneity of patents, depending on the fixed effects combination, I find that brown patents tend to increase emissions even as they slow their growth rate. Green patents meanwhile, might tend to lower emissions. When correcting for endogeneity, however, only the first of these holds. Further, the estimated elasticity increases by an order of magnitude. There, the estimates suggest that a one percent increase in the stock of brown patents increases emissions of greenhouse gases by around 0.4 percent. A similar result is found for carbon dioxide and suspended particulates (although the latter estimates are far smaller in magnitude and significance). Thus, the estimates suggest that not only do OLS estimates suffer from endogeneity bias but that there is no compelling evidence that patenting – including green patents – lowers emissions in a meaningful way.

The paper is laid out as follows. The next section provides a brief overview of the literature on innovation and emissions which is intended to couch my contribution. In Section 3, I discuss the econometric approach and the data used. In particular, I provide the specifics of the instrumenting approach. Section 4 provides the results on the impact of patents on pollution. Section 5 concludes.

## 2 Literature Review

The work on the drivers and mitigating factors of emissions is a large one and I do not attempt to provide a comprehensive overview of it here. Even the subset of the literature looking at the relationship between innovation and emissions is a sizable body of work with different papers using data from different countries and/or industries.

The general presumption is that more innovation leads to lower emissions since newer technologies tend to embody features such as improved energy efficiency. Further, specifically green patents would hopefully achieve the environmental benefits their name suggests. That said, the reverse can also be true. For example, although there has been a recent boom in patents related to artificial intelligence (see Buarque et al. (2020) for discussion), such technologies are notoriously polluting (see Yu et al. (2024) for recent specifics). Thus, more patenting may actually lead to *more* emissions. Further, there is concern over so-called "greenwashing" in which firms' innovation pays lip-service to environmental concerns but does little to create meaningful change.

Thus, there is a need for careful estimates that link innovation and pollution outcomes. The most straightforward approach to the issue uses some measure of environmental pollution as the dependent variable and a measure of innovation as the key explanatory variable (see, e.g. Cheng et al. (2021), Du et al. (2019), or Pata et al. (2024)). Overall, the primary pollutant studied is carbon dioxide (CO2) however some, such as Bianchini et al. (2023), instead using a composite measure across various greenhouse gases (GHG) that includes CO2 as one of its components.[1] Examples using a composite GHG measure include Bianchini et al. (2023) while those using CO2 include Erdoğan et al. (2020), Wang et al. (2012), and Tan & Cao (2023). Turning to measuring innovation, by far the most common method is to use patent data (see Haščič & Migotto (2015) for discussion). Patent data certainly has its challenges in that not all useful innovations are patented and it measures an outcome of the highly uncertain research process rather than its inputs, its ubiquity lies in its ready availability.

On the whole, the results from this literature might be called "promising" in that, generally, more innovation appears to be linked to lower levels of emissions (although this is

[1]Rather than focussing on emissions, Khan et al. (2022) and He et al. (2018) consider the impact of innovation on the production of renewable energy in Germany and China respectively. They find that more innovation leads to more green energy production.

certainly not universal; see e.g. Pata et al. (2024) or Cheng et al. (2021)). That said, a major issue with much of this literature, is the possibility that innovation activity is endogenous. For example, it may well be that, high emissions prompt research that results in patents. Alternatively, there may be uncontrolled for factors such as consumer sentiment which, when emissions rise, exacerbate greenwashing incentives.

One way to bypass this is to use policy changes as a way of instrumenting innovation, an approach taken by Lambrecht & Willeke (2025) and Scotti et al. (2025).[2] Bianchini et al. (2023) also use an IV approach but rather than relying on policy, they use measures of political orientation and institutional quality as instruments. Alternatively, one can skip the link via innovation step entirely and directly examine the impact of policy on emissions (see Dechezleprêtre et al. (2023) or Colmer et al. (2024) for examples). Endogeneity, however, remains an issue since policy is arguably developed in response to unacceptably high emissions. Further, in many cases policies and other potential instruments are at the country (or region) level and do not differentiate across industries.

A second approach is to rely on lagged values of innovation in a country/industry to instrument for current values (as is done in estimators such as SYS-GMM which was employed to this effect by Huang et al. (2021) and Többelmann & Wendler (2020)). Here, the challenge is that patenting activity is infrequent. As such, single-year patent measures are often zero, particularly when working at the industry level. As a further consequence, cross-year patent stocks move slowly, suggesting that prior values may suffer from comparable endogeneity issues as the contemporaneous value. Other approaches include estimators such as the autoregressive distributed lag model used by Alexiou (2025), Ghorbal et al. (2024), and Radulescu et al. (2025) or the fixed effect panel quantile method used by Li et al. (2021) and Cheng et al. (2019). These, however, do not directly address the underlying problem.

Thus, there is still a need for the development of instruments for patenting in order to

[2] This is then related to the work examining the drivers of green innovation. See Martínez-Zarzoso et al. (2019), Calel & Dechezleprêtre (2016), Noailly & Smeets (2015), Barbieri (2015), and Bel & Joseph (2018) for an examples.

better establish whether there is a causal effect of patenting on environmental outcomes. This is the primary contribution of this paper – introducing a novel instrument that varies across countries and industries and is based on patent citations. Before describing this in detail, it is worth recognizing the recent contribution of Hege et al. (2025). Using data from the US, they consider how the impact of supplier climate innovation impacts emissions on downstream customers. To deal with the endogeneity of supplier patents, they use a measure of technology obselecense (which also motivates my use of finitely-lagged patent stocks) and patent examiner stringency (that is, the overall approval rate of the randomly assigned officer to an application). This latter, however, is not possible in the European data I use since this individual is not revealed by the European patent office. Thus, my approach is complementary to theirs.

# 3 Empirical Approach and Data

The goal is to estimate the impact of patenting activity on emissions at the country-industry level. In particular, I am interested in examining whether so-called "green" patents differ from non-green, or "brown", patents. With this in mind, I estimate the following equation:

$$Pollutant_{cst} = Brown_{cst-1} + Green_{cst-1} + X_{cst-1} + \Gamma_{ict} + \varepsilon_{cst} \tag{1}$$

where $Pollutant_{cst}$ is a measure of emissions in country $c$'s sector $s$ in year $t$, $Brown$ is a measure of non-green patenting activity, $Green$ is amount of green patenting activity, $X$ is a vector of additional controls, $\Gamma$ is a set of fixed effects, and $\varepsilon$ is the error term.

## 3.1 Emissions Data

I use data on three different types of emissions. Given that the existing literature focuses on either greenhouse gas (GHG) or carbon dioxide (CO2) emissions, I include both of these as dependent variables. Note that GHG measure combines CO2, nitrous dioxide (N2O), methane (CH4), and hydrofluorocarbons (HFC) in CO2 equivalents. In addition, I include emissions of suspended particulates (SPM) below 2.5 microns as a non-gas emissions.[3] All three pollutants are measured in tons and normalized by country-industry value added (itself measured in millions of Euros). This normalization thus controls for simple scale effects. Finally, to deal with skewed distribution of emissions across sectors and countries and provide a elasticity interpretation to the estimated coefficients, I take the inverse hyperbolic sine (IHS) of the value. This approach is similar to taking the natural log but allows for zero values.[4] These data are available from 1995 to 2024, however I end the estimation sample in 2019 both because of issues in the patent data (described below) and because of the abnormally low emissions from 2020-2022 as a result of Covid lockdowns. These data, along with value-added, are obtained from Eurostat.[5]

Figure 1 illustrates the total GHG emissions for the 27 countries in the sample from 1995-2019. This illustrates not only the variation across countries (which are listed along the horizontal axis) but also the role of normalizing by value-added since, although large countries like France and Germany emit the most in tons, they also provide large value added. Figure 2 does the same for the 20 industries in the sample. Again, normalization by value-added tends to increase the total in low value-added industries. Note that, as described below, I restrict the sample to 20 manufacturing industries because of the patent data.

As an alternative to this "level" of emissions, I also use the growth rate of emissions between $t$ and $t-1$ as a dependent variable. This alternative may help identify the environmental benefits of innovation if, even though patents may not bring emissions down, they may reduce the growth in emissions.

[3]SPMs have a well-established link to lung problems (Kyung & Jeong 2020).

[4]Specifically, for a value $x$, the IHS of $x$ is $ln\left(x + \left(x^2 + 1^{0.5}\right)\right)$. The issue of zeros is more prevalent in the patenting data, especially green patents. Nevertheless, I use this transformation throughout for consistency.

[5]These are found at `https://ec.europa.eu/eurostat`.

### 3.2 Patent Data

Patent data is obtained from PATSTAT.[6] This database contains all patent applications to the European Patent Office (EPO), the US Patent Office, and the offices of China, Japan, and Korea. Given the delays and variation in granting patterns across sectors, I include all patent applications, not just those which are granted. Each patent is part of a patent family, a designation that avoids double counting for repeat applications across patent offices as well as to a given patent office. Thus, when I use the term patent, I am referring to the patent family. Each patent needs to be assigned to one or more countries and industries. To assign a patent to a country, I use fractional apportionment so that the share of a patent attributed to a country equals the share of inventors from that country. Likewise, I use PATSTAT's fractional apportionment that assigns patents to NACE rev.2 industries. Note that as this only considers manufacturing industries, my analysis likewise considers only emissions by manufacturing. Each patent is assigned to a single year using the earliest filing date within the family.[7] Thus, by multiplying the country share and inventor share, I can allocate a given patent to a set of country-industries.

Further, each patent is designated as brown or green. Green patents are those where the patent office assigns it either the Y02 or Y04S technology codes. Under the Cooperative Patent Classification (CPC) system, patents with a Y02 designation are those aimed at mitigation or adaptation against climate change. The Y04S designation meanwhile indicates a technology designed to improve the generation, transmission, distribution, management, and usage of electrical power. Thus, any patent with one of these CPC codes is a green patent; those without them are brown patents.

Finally, these can be summed up within a given year to give the flow of new applications in year $t$. Figure 3 shows the number of brown (top panel) and green (bottom panel)

[6] Specifically, I use the Autumn 2022 version which was obtained from `https://www.epo.org/en/searching-for-patents/business/patstat`.

[7] By using the filing date, this places a patent in time near to its first use since, by EPO regulation, applications must be filed within six months of first use. An alternative is to use the first publication date, a date that indicates when the application is first revealed to the public.

patents from 1980-2022. There are two things to note from this. First, after 2019, there is a marked drop-off in the number of patents due to lags in applications entering the PATSTAT database. This, along with the Covid-related emissions drop during lockdown, motivates ending the estimating sample in 2019. Second, there are far more brown than green patents. In particular, green patenting was very low until around 2005. This sudden increase has led to concerns over "greenwashing" in which patents are labelled as green for public relations purposes rather than technological content or environmental efficacy.

Comparing the number of patents across countries (Figure 4 or industries (Figure 5) shows clear variation with some countries (e.g. Germany and France) and industries (e.g. Chemicals or Machinery) producing more patents of both types. It is worth noting, however, that, relatively, Computers, Electronics, and Optical equipment produces relatively few green patents whereas the reverse is true for Electrical Equipment.

Since it is reasonable to assume that there is a lag between a patent application and the inventions potential impact on emissions, for the explanatory variables, I define the stock of patents as the sum of applications across a ten year period.[8] Specifically, $Brown_{cst}$ is the (IHS) sum of patents from $t$ to $t-9$ with $Green_{cst}$ defined similarly.[9] Note that both of these are lagged one year. Figure 4 illustrates the number of brown and green patents by country across the sample. Note that since country-year features such as population are automatically accounted for by the fixed effects, then it is valid to interpret the patent stock as the number of patents per capita as in Mensah et al. (2018).

In unreported alternative results, rather than the number of patents in a given country-sector-year, I use the number of forward citations those patents receive. This is one approach to dealing with heterogeneity in the influence (i.e. quality) of patents. This approach yields results similar to those reported here with the exception that. I do not, however, use these as my main results because of vintage effects. Since citations accumulate over time, the

[8]This is in contrast to Weina et al. (2016) who use a discounted sum of patents where the discount rate is 0.1.

[9]To be clear, this is the sum of IHS, not the IHS of the sum.

total number of citations declines as one approaches the end of the sample even as emissions rise. Thus, this approach may arguably be more prone to spurious negative correlations. Nonetheless, they are available on request.

### 3.3 Additional controls

Although normalizing emissions by value-added is intended to help control for scale (as well as compare the damaging emissions to the benefit they create), two additional variables are included to control for scale. The first is the (IHS) of capital by country-industry-year, measured in millions of Euros. The second is the total employee compensation, also measured in millions of Euros. Further, since both of these are log functions, this helps to control for changes in the capital-labour ratio over time.

To control for country-time varying factors, all specifications include country-year fixed effects. Depending on the specification, I also include either industry (two-digit NACE), industry-year, or industry-year and country-industry fixed effects. This latter places a very large burden on changes in the patent stock over time for identification. Since patenting is not overly frequent, meaning that the stock of patents in a country-industry is fairly constant over time, this demanding set of fixed effects may be expected to negatively impact the estimated significance of patenting.

Finally, the error term is clustered by country-industry.

### 3.4 Instrumental variable approach

As discussed above, one of the primary issues when estimating a causal effect of patenting on emissions is the possibility of endogeneity. This can occur either because of reverse causality (where higher emissions drive innovation efforts) or omitted variables (wherein some uncontrolled for factor leads to both higher emissions and more patenting). The most obvious way to address this is to use an instrumental variables (IV) approach to instrument for the stock of brown and green patents. The challenge to this, however, is to identify exogenous variables which impact country-industries differently. While policies might be exogenous, they equally may be endogenous since they may be in response to high emissions. Further, many policies are country-wide, so that they do not provide the necessary country-industry level variation.[10] Finally, if one wishes to focus on the specific impact of green patents as compared to patenting overall, estimation requires a second instrument.

With this in mind, I use the patent data to construct two instruments which fit these criteria. I do so following the shift-share approach of Bartik (1991). As discussed by Borusyak et al. (2025), shift-share instruments have gained popularity both because of their econometric properties but also because of their intuitive nature. In the current context, the instruments build from the idea that country-industries are differentially exposed (the "share") to an outside shock (the "shift").

With this in mind, my shift, $\omega^{l}_{is,rt}$, is constructed from the backward citations in patents from country-industry $is$ to country-industry $jr$ in "colour" $l$ (brown or green). Citation data comes from PATSTAT. To ensure exogeneity of these citations, I use only citations from patents filed between 1980 and 1990. As before, citations are allocated to $is, jr$ pairs using fractional apportionment. I eliminate those where the citing and cited patents have a positive inventor share from the same country. Thus the share for all of $i$'s industries only involves patents that do not involve $i$. Note that this also eliminates within-family citations. Further, the citations are separated according to whether the patent in $jr$ is green or brown. Note that I do not make this separation according to the colour of $is$'s patents. This is because, as illustrated in Figure 3, there are fairly few green patents during the 1980s, meaning that in such a decomposition, there would be a large number of zeros. Nevertheless, there are some zeros remaining (driven by the fact that some countries do not record patents in certain sectors that contain cross-border citations). In this case, I construct the average number of backward citations from $i$'s sectors other than $s$ to $jr$ and the average number of citations from countries other than $i$ and $j$ but in sector $s$ to $jr$. If both of these are non-zero, then

[10] This does not mean, however, that industry-specific policies do not exist. However, when they do exist, they are quite likely in response to an industry-specific market failure, i.e., the policy is endogenous.

I average them and use this for $\omega^l_{is,rt}$. If only one is positive, then I use that one. Thus, my shift measure is $\omega^l_{is,rt} = Cites^l_{is,rt}$ where $l$ is either brown or green patents in $rj$ and $Cites$ is the (fractionally-apportioned) number of backward citations made by $is$ for patents in $jr$ for patents filed in $js$ between 1980 and 1990 (with the modification when there are no citations between $is$ and $jr$). This then captures the exposure of a given country-industry to that of another since, as is discussed in e.g. Davies & Yang (2024), knowledge builds on knowledge.

My "shift" variable is the stock of patents of a given colour in country-sector $jr$ as of year $t$. As before, I use the ten year stock of patent applications (fractionally apportioned). Note that this again excludes patents with inventors in country $i$. Thus, I have two instrumenting shift-share variables:

$$Brown^{IV}_{ist} = \sum_{j \neq i} \sum_{r} \omega^B_{is,jr} Brown_{jst} \tag{2}$$

and

$$Green^{IV}_{ist} = \sum_{j \neq i} \sum_{r} \omega^G_{is,jr} Green_{jst} \tag{3}$$

which capture the historical exposure of $is$ to the patents in $jr$ and the current stock of patents of each colour in $jr$. Intuitively, when a given $jr$ produces more patents, this should increase patenting activity in other country-industries, with a stronger effect in those that, due to linguistic, migration, trade, or other reasons, draw more inspiration from the patents of $jr$. As discussed by Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020), when either the shift or the share is exogenous, this is sufficient for the exogeneity of the instrument. Since the shares are constant and are fixed before the start of the sample, they are plausibly exogenous. Although the shift variable is lagged one period to match the patent data in Equation 1, common trends across countries and industries make such an exogeneity claim less convincing on its behalf.

Summary statistics are found in Table 1. The list of countries and industries are shown in Figures 1 and 2. Note that while Eurostat provides data for the entire EU27, Iceland, Norway, and Switzerland, my sample is somewhat smaller. This is because patent data for Estonia, Lithuania, Latvia, Slovakia prior to 1990 are not reported by PATSTAT. Also, for clarity, note that the UK is not included in Eurostat.

# 4 Results

In Tables Tables 2, 4, and 5 I report estimates for each of the pollutants – GHG, CO2, and SPM respectively (Table 3 presents the first stage estimates from the IV approach). In each, I employ both OLS (the top panel) and IV estimators (the bottom panel). Further, I do so using both the (IHS) level of emissions (columns 1-3) and their growth rate (columns 4-6). Finally, for each of these, I employ different combinations of fixed effects as indicated at the bottom of the tables.

## 4.1 Greenhouse gases

I begin with the GHG results of Table 2. Starting with the OLS results in the top panel, brown patents do not appear to have much of a relationship to emissions. If there is a relationship, the results when including country-year and country-industry fixed effects suggest suggest that a 1 percent increase in the number of brown patents increases emissions by 0.04 percent (column 2) but slow the growth rate by 0.012 percent (column 5). Although green patents typically have a negative coefficient, I only obtain a significant coefficient in column 1 where the fixed effects are the least demanding. There, the estimates suggest that a 1 percent increase in the number of green patents lowers GHG emissions by 0.04 percent. In terms of the additional controls, country-industries with more capital appear to emit more (a result that can also be interpreted as higher emissions from those which are more capital intensive). Higher compensation, meanwhile, tends to increase the growth rate of emissions.[11] Comparing the R-squared values across the fixed effects combinations, when looking at levels, there is a significant gain in explanatory power when replacing industry with country-industry fixed effect (moving from column 1 to column 2). The additional gain when adding industry-year fixed effects is minor. Thus, for emissions, column 2 may be the most preferred specification. When looking at growth rates, however, including industry-year fixed effects significantly increases the explanatory power.

The natural concern with these results is the potential endogeneity of the patent variables. With this in mind, the bottom panel instruments for the stock of brown and green patents using the shift-share instruments. Before looking to the resulting estimates, it is important to examine the validity of the instruments. Table 3 presents the first-stage results for brown patents (columns 1-3) and green patents (columns 4-6) across the three different fixed effects combinations.[12] The brown links to patenting elsewhere is positive and strongly significant except in columns 3 and 6 with the most demanding fixed effects specification. Given that patenting activity is fairly infrequent, it may be that the inclusion of industry-year fixed effects, alongside country-year and country-industry, simply does not leave much variation for the instruments to capture. Green links are significant on two occasions. This may result from the infrequency of green patents during the 1980s (and therefore few citations). Returning to Table 2, the bottom panel reports the Cragg-Donald Wald F-statistic. Given that there are two endogenous variables, This should be compared to the Stock-Yogo weak identification test. In this sample, the critical value is 7.03. This threshold is exceeded when using country-year and industry or country-year and country-industry fixed effects. Thus, at least in those cases, it seems that the instruments are suitable.

Turning to the causal impact of patents on emissions, the prior pattern for brown patents holds. Further, the coefficients are generally larger. In column 2 (the preferred specification from OLS), the estimates now suggest that a 1 percent increase in the number of brown

[11] In unreported results without these controls, results were very similar. These are available on request.

[12] Note that since the growth regressions only change the dependent variable, this does not affect the first stage results.

patents increases emissions by 0.44 percent. Likewise, although it is only marginally significant, the estimates of column 5 suggest that emissions growth slows by 0.06 percent following a 1 percent increase in brown patenting. For green patenting, however, there is now no significant estimated coefficient in any specification.

Combining these results suggests that the claims that innovation can mitigate emissions may be misplaced since the OLS estimates may well suffer from endogeneity bias. The hopeful effects for green patents on the level of emissions and brown patents on the growth of emissions evaporate when dealing with endogeneity. Further, the potential for brown patents to increase pollution may be understated. When combined with the ineffectiveness of green patents, this suggests the potential for greenwashing.

## 4.2 CO2 and Suspended Particulates

Table 4 presents comparable results when using emissions of just CO2, rather than those of the composite GHG. Given the importance of CO2 in that composite, it is unsurprising that the estimates follow those of Table 2 very closely.

The estimates for SPM in Table 5 also follow a similar pattern. Overall, the estimated coefficients are far smaller than for the gases in Tables 2 and 4. When using OLS, only brown patents show some potential effects where the strongest indication is again in column 5 which suggests that more brown patents reduces the growth rate of emissions. When using IV, however, as before, that largely disappears. It is also worth noting that when using IV, I again find a (marginally) significant result for brown patents in column 2.

Thus, when using these alternative pollutants, I again find little to suggest that patenting, be that green or brown, does much to curb emissions.

# 5 Conclusion

In the race to avoid, or at least prepare for, the worst effects of climate change many leading minds argue for a leading role for technological innovation. Those hopes, however, must be supported by data since it is not clear that more innovation necessarily lowers emissions. A major challenge in providing such empirical answers is the likely endogeneity of patenting activity, one which even using policy changes may not resolve. With that in mind, this paper offers a new approach that bases a shift-share instrument on patent citations. Given that knowledge builds from knowledge (Davies & Yang 2024), by using long lags of backward citations, this permits the construction of a plausibly exogenous and well-performing instrument.

Although OLS estimates suggest some potential environmental benefits of innovation, especially when measured as green patents, after implementing the endogeneity correction, I find no such supporting evidence. In contrast, if there is an impact of patenting to be found, it seems that more brown patenting may increase emissions with an elasticity reaching as high as 0.4.

Rather than concluding with such a dismal result, it is important to recognize that these findings do not mean that innovation has *zero* capability to mitigate pollution. In particular, my estimates are at the country-industry level. This aggregation may conceal positive environmental outcomes from patenting at the level of regions or individual firms; alternatively, it may be that some industries see a benefit that the average does not.[13] In addition, it must be remembered that patents are only one measure of innovation; others may have more clear environmental benefits. However, the estimates do caution against relying on such advances to diffuse widely and have major reductions in emissions. While technological advancement will certainly play a part in mitigating the extent and effects of climate change, it is unlikely to achieve the necessary results on its own.

[13]See, for example, the sector-specific studies of Barbieri (2015) or Lambrecht & Willeke (2025).

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Figure 1: Greenhouse gases by Country (1995-2019)

Figures/gases_by_country.png

Figure 2: Greenhouse gases by Industry (1995-2019)

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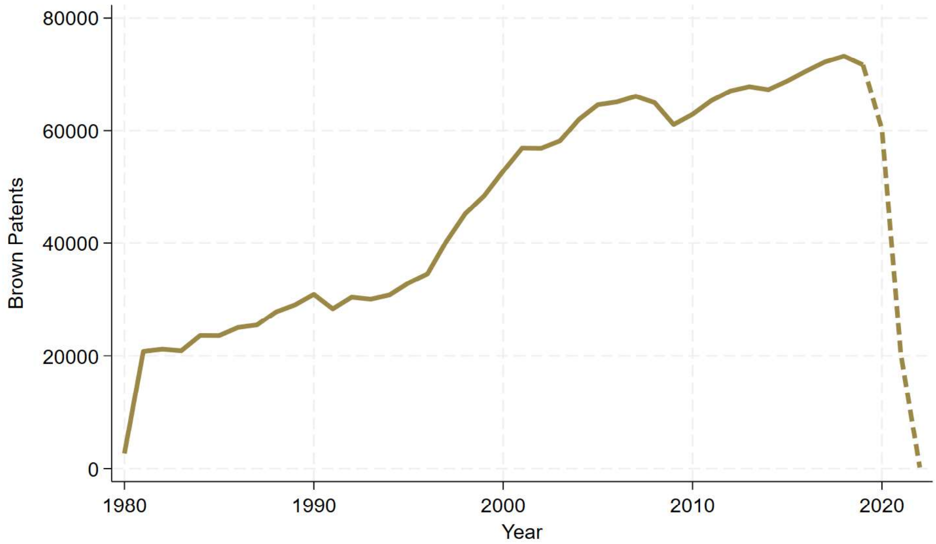
Figure 3: Patents over Time

(a) Brown Patents




(b) Green Patents

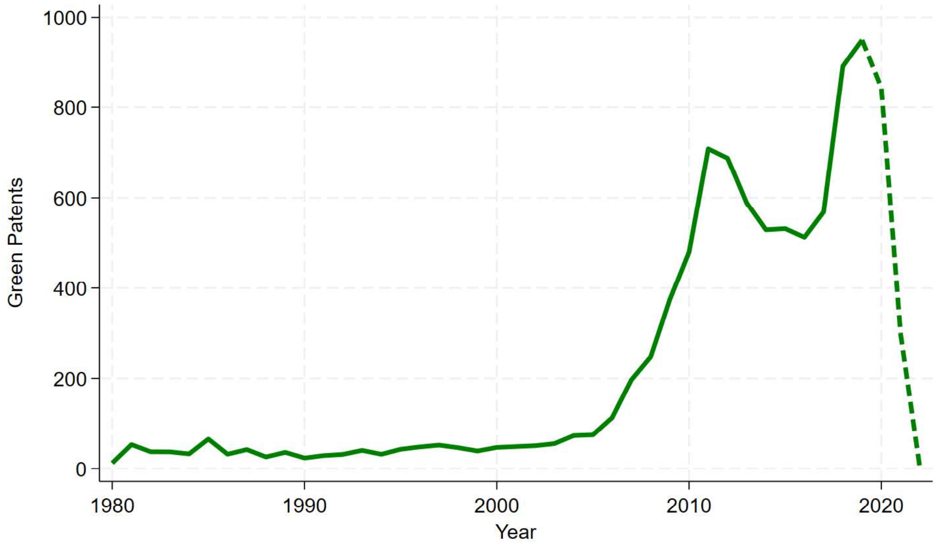


Figure 4: Patents by Country (1995-2019)

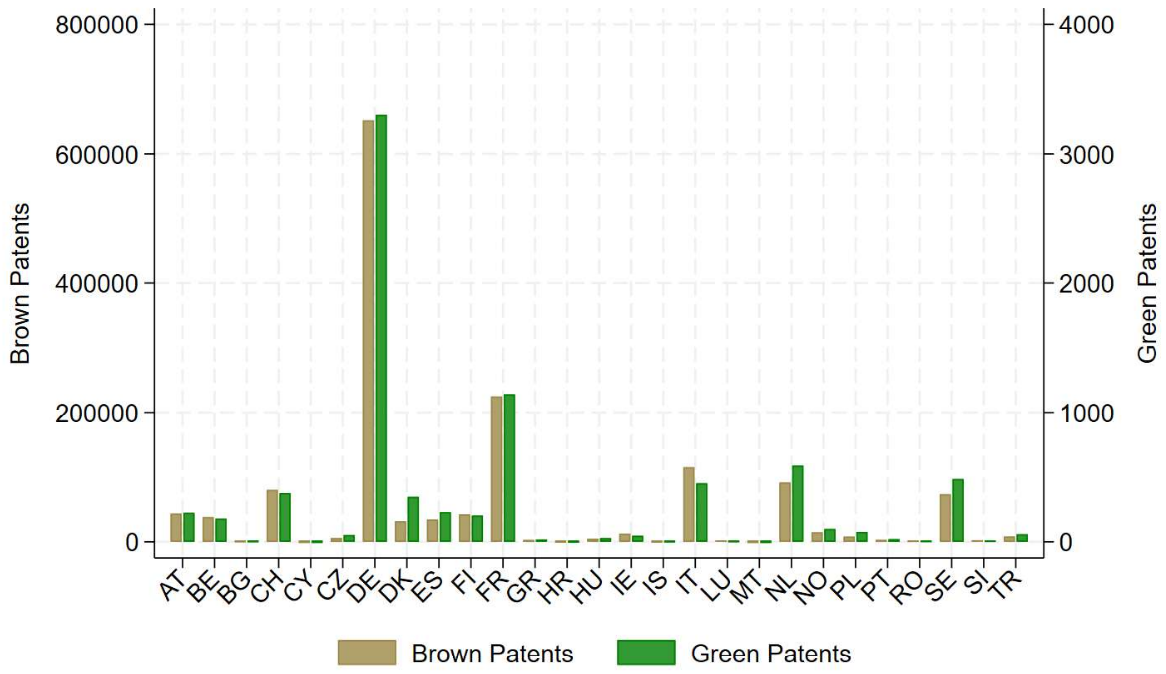


Figure 5: Patents by Industry (1995-2019)

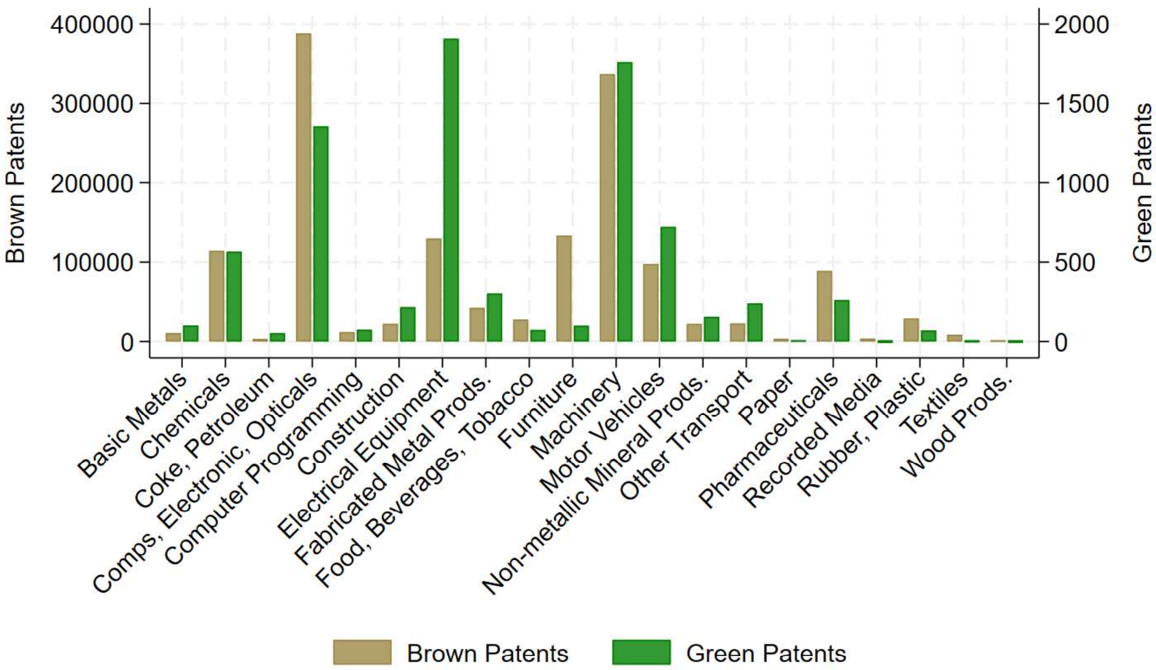


Table 1: Summary Statistics

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| CO2 | 6,757 | 0.426 | 0.737 | 0 | 4.608 |
| Greenhouse Gasses | 6,757 | 0.451 | 0.752 | 0 | 4.611 |
| SPM | 6,577 | 0.000217 | 0.000729 | 0 | 0.0163 |
| Capital | 6,757 | 5.868 | 1.982 | 0 | 11.20 |
| Compensation | 6,757 | 7.037 | 1.950 | 0 | 12.01 |
| Brown Patents | 6,757 | 4.750 | 2.629 | 0 | 11.86 |
| Green Patents | 6,757 | 0.817 | 1.311 | 0 | 7.129 |
| Brown Links | 6,757 | 16.23 | 2.704 | 6.144 | 23.75 |
| Green Links | 6,757 | 10.79 | 1.928 | 0 | 15.55 |

*Notes*: The sample corresponds to that of column 1 of Table 2.

Table 2: Greenhouse Gas Emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | | Levels | | | Growth Rate | |
| **OLS** | | | | | | |
| Brown Patents | 0.0254 | 0.0435** | 0.00996 | -0.00205 | -0.0123** | -0.00418 |
| | (0.0263) | (0.0216) | (0.0167) | (0.00214) | (0.00571) | (0.00643) |
| Green Patents | -0.0448*** | -0.00574 | -0.000813 | -0.000979 | 0.00229 | 0.00233 |
| | (0.0158) | (0.00918) | (0.0121) | (0.000964) | (0.00269) | (0.00470) |
| Capital | 0.109*** | 0.0328 | 0.0121 | -0.00605* | -0.0221 | -0.0205 |
| | (0.0361) | (0.0215) | (0.0192) | (0.00358) | (0.0159) | (0.0149) |
| Compensation | -0.0112 | -0.0175 | 0.000117 | 0.00999** | 0.0445*** | 0.0508*** |
| | (0.0461) | (0.0383) | (0.0385) | (0.00394) | (0.0164) | (0.0167) |
| R-squared | 0.783 | 0.964 | 0.975 | 0.095 | 0.113 | 0.260 |
| **IV** | | | | | | |
| Brown Patents | 0.156 | 0.437*** | 0.271 | 0.0218 | -0.0620* | -0.139 |
| | (0.276) | (0.167) | (4.021) | (0.0236) | (0.0338) | (0.450) |
| Green Patents | -0.161 | 0.0190 | 1.080 | -0.00306 | -0.00480 | -0.0607 |
| | (0.220) | (0.0893) | (4.758) | (0.0163) | (0.0285) | (0.525) |
| Capital | 0.126** | 0.00921 | 0.00245 | -0.00740 | -0.0164 | -0.0156 |
| | (0.0513) | (0.0349) | (0.0785) | (0.00465) | (0.0161) | (0.0248) |
| Compensation | -0.0397 | -0.188*** | 0.0433 | 0.00392 | 0.0652*** | 0.0568 |
| | (0.0782) | (0.0727) | (0.654) | (0.00695) | (0.0221) | (0.0624) |
| Cragg-Donald F | 12.58 | 53.85 | 0.335 | 11.74 | 52.80 | 0.392 |
| Observations | 6,757 | 6,755 | 6,735 | 6,374 | 6,372 | 6,372 |
| *Fixed Effects* | | | | | | |
| Country-Year | Y | Y | Y | Y | Y | Y |
| NACE | Y | | | Y | | |
| Country-NACE | | Y | Y | | Y | Y |
| NACE-Year | | | Y | | | Y |

*Notes*: Standard errors clustered by country-industry are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The Stock-Yogo weak ID test critical value for a 10% bias is 7.03.

Table 3: First Stage Estimates

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Patents: | | Brown | | | Green | |
| Brown Links | 0.0457*** | 1.711*** | 0.269 | 0.0869*** | 0.761** | 0.219 |
| | (0.0141) | (0.333) | (0.386) | (0.0148) | (0.345) | (0.344) |
| Green Links | -0.0389** | 0.0646 | -0.00763 | -0.0149 | 0.298** | 0.0150 |
| | (0.0169) | (0.0398) | (0.0349) | (0.0175) | (0.118) | (0.0857) |
| Capital | 0.0731 | 0.00823 | 0.0178 | 0.220*** | 0.0945* | 0.00236 |
| | (0.0581) | (0.0725) | (0.0465) | (0.0585) | (0.0495) | (0.0460) |
| Compensation | 0.259*** | 0.429*** | 0.0929 | 0.0530 | 0.132** | -0.0600 |
| | (0.0638) | (0.112) | (0.0854) | (0.0681) | (0.0663) | (0.0713) |
| Constant | 2.176*** | -26.79*** | -0.297 | -2.099*** | -16.23*** | -2.484 |
| | (0.436) | (5.514) | (6.325) | (0.486) | (5.643) | (5.622) |
| Observations | 6,757 | 6,755 | 6,735 | 6,757 | 6,755 | 6,735 |
| R-squared | 0.955 | 0.989 | 0.992 | 0.757 | 0.932 | 0.958 |
| *Fixed Effects* | | | | | | |
| Country-Year | Y | Y | Y | Y | Y | Y |
| NACE | Y | | | Y | | |
| Country-NACE | | Y | Y | | Y | Y |
| NACE-Year | | | Y | | | Y |

*Notes*: Standard errors clustered by country-industry are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: CO2 Emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | | Levels | | | Growth Rate | |
| **OLS** | | | | | | |
| Brown Patents | 0.0242 | 0.0350* | 0.0114 | -0.00212 | -0.0125** | -0.00580 |
| | (0.0255) | (0.0207) | (0.0169) | (0.00215) | (0.00576) | (0.00612) |
| Green Patents | -0.0435*** | 0.00378 | 0.00283 | -0.00132 | 0.00147 | 0.00301 |
| | (0.0156) | (0.00804) | (0.0113) | (0.00102) | (0.00257) | (0.00439) |
| Capital | 0.108*** | 0.0399* | 0.0211 | -0.00464 | -0.0182 | -0.0172 |
| | (0.0360) | (0.0207) | (0.0193) | (0.00352) | (0.0151) | (0.0139) |
| Compensation | -0.0135 | -0.0192 | -0.000777 | 0.00882** | 0.0427*** | 0.0487*** |
| | (0.0468) | (0.0361) | (0.0371) | (0.00389) | (0.0161) | (0.0162) |
| R-squared | 0.780 | 0.966 | 0.975 | 0.091 | 0.112 | 0.261 |
| **IV** | | | | | | |
| Brown Patents | 0.214 | 0.332** | 0.228 | 0.0176 | -0.0534** | -0.115 |
| | (0.289) | (0.153) | (4.454) | (0.0230) | (0.0271) | (0.398) |
| Green Patents | -0.211 | 0.0372 | 1.216 | -0.00116 | -0.00327 | -0.0565 |
| | (0.230) | (0.0833) | (5.262) | (0.0159) | (0.0269) | (0.472) |
| Capital | 0.132** | 0.0202 | 0.0117 | -0.00621 | -0.0137 | -0.0133 |
| | (0.0538) | (0.0289) | (0.0859) | (0.00456) | (0.0151) | (0.0223) |
| Compensation | -0.0549 | -0.150** | 0.0548 | 0.00371 | 0.0597*** | 0.0530 |
| | (0.0818) | (0.0663) | (0.724) | (0.00674) | (0.0201) | (0.0559) |
| Cragg-Donald F | 12.58 | 53.85 | 0.335 | 11.74 | 52.80 | 0.392 |
| Observations | 6,757 | 6,755 | 6,735 | 6,374 | 6,372 | 6,372 |
| Fixed Effects | | | | | | |
| Country-Year | Y | Y | Y | Y | Y | Y |
| NACE | Y | | | Y | | |
| Country-NACE | | Y | Y | | Y | Y |
| NACE-Year | | | Y | | | Y |

*Notes*: Standard errors clustered by country-industry are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The Stock-Yogo weak ID test critical value for a 10% bias is 7.03.

Table 5: Suspended Particulate Matter Emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var.: | | Levels | | | Growth Rate | |
| **OLS** | | | | | | |
| Brown Patents | 5.55e-05 | 2.28e-05 | -4.91e-05* | -5.41e-06 | -2.40e-05** | -1.11e-05 |
| | (3.59e-05) | (4.74e-05) | (2.82e-05) | (3.81e-06) | (9.62e-06) | (1.17e-05) |
| Green Patents | -1.55e-05 | -1.21e-05 | -6.87e-06 | -1.93e-06 | 5.49e-06 | 1.01e-05 |
| | (2.99e-05) | (2.05e-05) | (1.62e-05) | (3.15e-06) | (4.77e-06) | (9.10e-06) |
| Capital | 0.000112** | 0.000121 | 4.43e-05 | -4.64e-06 | -1.69e-05 | 1.22e-05 |
| | (4.41e-05) | (9.35e-05) | (2.80e-05) | (5.15e-06) | (2.13e-05) | (1.97e-05) |
| Compensation | -3.50e-05 | -7.14e-05 | 4.12e-05 | 5.08e-06 | 5.01e-05** | 3.68e-05* |
| | (4.92e-05) | (9.09e-05) | (4.77e-05) | (5.39e-06) | (2.25e-05) | (2.18e-05) |
| R-squared | 0.293 | 0.796 | 0.919 | 0.065 | 0.093 | 0.409 |
| **IV** | | | | | | |
| Brown Patents | -0.000543 | 0.00113* | 0.000485 | 1.51e-05 | -0.000218* | -8.70e-05 |
| | (0.000787) | (0.000661) | (0.00207) | (3.51e-05) | (0.000121) | (0.000250) |
| Green Patents | 0.000505 | -0.000175 | 0.000617 | -3.77e-06 | -1.49e-06 | 9.53e-05 |
| | (0.000651) | (0.000199) | (0.00269) | (3.18e-05) | (5.58e-05) | (0.000401) |
| Capital | 5.06e-05 | 5.77e-05 | 3.35e-05 | -6.23e-06 | 8.31e-06 | 1.83e-05 |
| | (8.80e-05) | (9.39e-05) | (8.52e-05) | (6.72e-06) | (2.80e-05) | (2.87e-05) |
| Compensation | 7.77e-05 | -0.000417 | 4.63e-05 | 4.43e-07 | 0.000105** | 4.88e-05 |
| | (0.000165) | (0.000279) | (0.000435) | (9.05e-06) | (4.74e-05) | (5.51e-05) |
| Cragg-Donald F | 9.669 | 51.38 | 0.452 | 8.837 | 49.04 | 0.512 |
| Observations | 6,577 | 6,575 | 6,575 | 6,174 | 6,172 | 6,172 |
| *Fixed Effects* | | | | | | |
| Country-Year | Y | Y | Y | Y | Y | Y |
| NACE | Y | | | Y | | |
| Country-NACE | | Y | Y | | Y | Y |
| NACE-Year | | | Y | | | Y |

*Notes*: Standard errors clustered by country-industry are in parentheses. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level. The Stock-Yogo weak ID test critical value for a 10% bias is 7.03.

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## ABOUT RETHINK-GSC

The project ‚Rethinking Global Supply Chains: Measurement, Impact and Policy' (RETHINK-GSC) captures the impact of knowledge flows and service inputs in Global Supply Chains (GSCs). Researchers from 11 institutes are applying their broad expertise in a multidisciplinary approach, developing new methodologies and using innovative techniques to analyse, measure and quantify the increasing importance of intangibles in global supply chains and to provide new insights into current and expected changes in global production processes.

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