Online Annexes

Green Innovation and Diffusion: Policies to Accelerate Them and Expected Impact on Macroeconomic and Firm-Level Performance

Staff Discussion Note No. SDN/2023/008

Online Annexes I-III provide information on data sources, methodology, and complementary results referenced in the main text.

Annex I. Data Sources and Sample Coverage

I.1. Patent Data Used in Cross-Country Analysis

The economic analysis on the cross-country macroeconomic effects of patent filings is based on ongoing work by Hasna and others (forthcoming a). The Staff Discussion Note (SDN) uses data on patent filings from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT),[1] which covers all patent applications from 92 application authorities worldwide until 2019. The database provides data on inventions (patents attributed to inventors' country of residence) and filings (patents attributed to the application authority in which it is seeking legal protection). This analysis will focus on patent filings as data coverage is more exhaustive than for inventions. In addition, patent filings are more likely to be associated with economic activity, since firms typically file for patent protection in the markets where they plan to operate; inventions relate more to the inventive capacity of the country. Therefore, the main measure of interest for this analysis is technological deployment proxied by patent filings.

Data Setup of Patent Filings: To avoid double counting within a country, patent filings are aggregated at the level of DOCDB families, which represent groups of patents covering the same invention.[2] To situate the patent family in time for the cross-country analysis, we use the earliest filing year in a given country. A patent for the same invention can also be filed in different countries, which is measured by the patent family size. A family size of two indicates that the patent family is filed in at least two countries, and so on.[3] In order to focus on higher-quality patents, the analysis will consider granted patents of family size two (i.e., filed in two or more countries).[4]

Identifying Green Filings: To proxy green patenting, the SDN first associates each patent family with a country and year as discussed above. It then refers to the patent technical classification from the Cooperative Patent Classification (CPC) codes to tag a patent as "green." The green tag is provided by the "Y02" CPC code, which flags patents that are related to climate-change-mitigating technologies (CCMTs). This class covers selected technologies that (1) control, reduce, or prevent anthropogenic emissions of greenhouse gases, in the framework of the Kyoto Protocol and the Paris Agreement, or (2) allow adapting to the adverse effects of climate change.

Time Coverage: Although some countries have patent filings available beginning in 1960, the coverage across countries improves only in the 1980s. To ensure proper cross-country comparisons, the time coverage is 1990–2019.

[1] Analysis is based on the fall 2022 edition.
[2] Different applications may cover slightly different claims but still the same invention within a country.
[3] For global time series analysis, a patent that has been filed in multiple countries will be counted only once. To place it in time, we refer to the earliest filing year of the patent globally.
[4] The analysis is restricted to granted patent filings for quality control, as the approval requirements for granting are tougher than the application requirements for a patent. The focus on family size greater or equal to two addresses concerns related to mass filings of low-quality patents in response to government incentivization programs, particularly in China.

Country Coverage: For the country coverage, the empirical analysis focuses on OECD and BRICS countries (subject to data availability), which cover more than 85 percent of global patent filings on average between 1990 and 2019.

I.2. Patent Data in the United States

The economic analysis on the economic effects of green innovation on economic activity in the United States is based on ongoing work by Hasna and others (forthcoming b). The SDN uses data on patent grants from the United States Patent and Trademark Office (USPTO) downloaded via PatentsView. The data include information such as patent application date, patent grant date, citations of other patents, patent assignees and their location, and classification according to the CPC and IPC systems.

Data Setup of Patent Filings: The data on total and green US patents filter for patent grants with at least one assignee located in the US. For the firm-level empirical analysis, patent grants were later assigned to US publicly listed firms (from COMPUSTAT) using a fuzzy match algorithm, which accounts for the variations, abbreviations, and misspellings of firm names in the granted patents data. A sample of matches were checked manually to ensure the reliability of the fuzzy match algorithm. Patent grants are aggregated to find the total number of patent grants by type for each firm in a given year.

Identifying Green Filings: Similarly to the macro setup, green patents are identified as green if they have the "Y02" tag under the IPC or CPC patent classification systems.

Time Coverage: The time coverage is 1980–2019.

I.3. Firm-Level Data in the United States

Firm-level data are based on the annual financial data for US publicly traded firms from COMPUSTAT. The data series used are revenue[5]; employees; gross property, plant, and equipment (PPE); net property, plant, and equipment; cost of goods sold; capital expenditure; book assets; location; Standard Industrial Classification (SIC) code; and North American Industry Classification System code. Following Kogan and others (2017), financial firms (SIC codes 6000 to 6799) and observations missing book assets are omitted from the sample.

I.4. Climate Policies

CPD data: Climate policy counts, from the Climate Policy Database, include policies with an explicit climate-change-mitigation objective, such as greenhouse-gas-emissions-reduction strategies; energy policies that help to decarbonize the energy supply and/or reduce energy demand; and policies that aim to introduce low-emissions practices and technologies to non-energy sectors, such as agriculture and land use. A policy can be a law, a strategic document, a target, or any other policy document that results in a lasting reduction of the country's emissions intensity (see Nascimento and others 2022). The main

[5] Revenue is deflated by the sectoral deflator series from the US Bureau of Economic Analysis (BEA), for which data are available from 1980 to 2022. If a firm cannot be matched to a sectoral deflator, the series is deflated by the GDP deflator from the US BEA (available from 1980 to 2022). Gross PPE, net PPE, and capital expenditure are deflated by the investment goods deflator from FRED (available from 1980 to 2022). Finally, book assets are deflated by the GDP deflator.

advantage of this measure, which has been used widely in scientific publications, is its comprehensive coverage of policy actions, both from an instrument and sectoral perspective. This is particularly important in a context where countries have resorted to sectoral policies and regulations and subsidies instead of economy-wide carbon pricing. One drawback of this measure is that it does not capture the intensity of each policy.

EPS: Parts of the SDN complement analysis using CPD data by using the OECD's Environmental Policy Stringency (EPS) Index. In contrast to CPD data, the EPS quantifies the stringency of a country's environmental policies. The index has three subcomponents: market-based measures, non-market-based measures, and technological support. Two limitations of the EPS are its relatively narrow country (33 countries) and instrument coverage.

I.5. Low-Carbon-Technology Imports and Tariffs

Data on low-carbon-technology (LCT) imports were obtained from the IMF's climate dashboard. The data report aggregate country-level imports at the 124 HS 5-digit codes. Low-carbon-technology products produce less pollution than their traditional counterparts and are considered to play a vital role in the transition to a low-carbon economy.[6]

Data on LCT tariffs are constructed by combining HS 5-digit codes associated with LCTs with product-level tariff data from the United Nations Conference on Trade and Development (UNCTAD) Trade Analysis Information System (TRAINS). LCT tariffs are constructed in steps. First, for each country and product line, a list of preferential partners/rates is identified. For all other partners, MFN tariffs are applied. After tariffs are properly assigned for each importing country–HS 5-digit code–partner triad, a trade-weighted average applied rate is constructed for each importing country–HS 5-digit code pair. Finally, we compute LCT tariffs by aggregating HS 5-digit codes corresponding to LCT goods.

Time Coverage: Time coverage is 1998–2019.

Country Coverage: The empirical analysis focuses on 136 countries with available LCT trade data for 20 or more years of data.

I.6. Foreign Direct Investment Data

Aggregate FDI data: Data on aggregate FDI flows come from the Financial Flows and Analytics (FFA) database constructed by the IMF's Research Department (see Bluedorn and others 2013 for a description and application of the database). The database contains information for 165 countries. It compiles data on capital flows from the IMFs Balance of Payments Statistics database and extends it with data from other sources, including Haver Analytics and the CEIC and EMED databases.

Bilateral greenfield FDI data: Data on greenfield FDI (GFI) come from the fDi Markets database. The data cover new cross-border projects and expansions of existing projects and are collected primarily from public sources (including newswires from tens of thousands of global media sources and over 3,000 promotion agency sources) and from market research and publication companies. Projects are then cross-

[6] https://climatedata.imf.org/documents/e46085cc97e445bb9c69e7de3bffbbac/explore.

referenced against multiple sources, especially investing firms' sources. GFI can differ from official FDI numbers because they exclude certain types of FDI (M&A other equity and nonequity investments); they include both announced and opened projects; and, in some instances, investment figures are not provided, in which case fDi Markets estimates the investment amount. Nevertheless, Aiyar, Malacrino, and Presbitero (2023) show that there is a strong correlation between country-level gross FDI flows and aggregate greenfield FDI values stemming from the fDi Markets database.

Importantly for the purpose of this SDN, fDi Markets provides detailed project-level information, which makes it possible to distinguish between different types of investments. In addition to information on the source and destination country, it provides information on the targeted sector and the type of activity pursued by the projects. In particular, the dataset classifies projects according to clusters and also tags projects with specific labels. The cluster and tags are used to create a "green" label. More precisely, in addition to all projects belonging to the "Environmental Technology" cluster, projects with a (1) alternative protein, (2) carbon capture, (3) cleantech, (4) cultured meats, (5) electric vehicles, (6) hydrogen, (7) photovoltaic, (8) plant-based foods, (9) vegan industries, (10) wind power technologies, (11) sustainable tourism, or (12) waste to energy tag are classified as green.

Time Coverage: While aggregate FDI data are available since the 1970s, the analysis is conducted for the 1990–2019 period. Greenfield FDI data are available since 2003.

Country Coverage: The empirical analysis focuses on 100 countries with available aggregate and greenfield FDI, as well as at least 15 years of greenfield FDI data.

Annex II. Empirical Frameworks

II.1. Macroeconomic Effects of Green Innovation—Cross-Country Study

Baseline Empirical Specification

The baseline regression analysis tackling the macroeconomic effects of green patent filings implements the local projection method proposed by Jordà (2005) to capture the dynamic impact of new patent filings at time t on real economic activity over multiple horizons. The specification is most related to work by Hasna, Hatton, and Mohaddes (2021) but with a focus on the short to medium term. The regression is conducted through the following specification:

$$\log Y_{i,t+h} - \log Y_{i,t-1} = \alpha + \beta_h \ \log P_{i,t}^{j} + \sum_{k=1}^{3} \lambda_{t-k}\, logP_{i,t-k}^{j} + \sum_{k=2}^{3} \mu_{t-k}\, logY_{i,t-k} + \eta_i + \nu_t + \epsilon_{it} \quad (1)$$

The dependent variable captures the percentage change in annual real GDP per capita in country i over the horizon h. The main independent variable is the logarithm of annual patents per capita of type j in country i where $j \in \{green\ patents,\ nongreen\ patents\}$. The coefficient β_h represents the effect of a 1 percent change in the flow of patents of type j in country i at time t on real economic activity in country i at time $t+h$. η_i is a country fixed effect, ν_t is a time fixed effect, and ϵ_{it} is the idiosyncratic error term. Standard errors are clustered at the country level.[7]

To expand on the role of green patents on economic activity, Annex III discusses results of a modified version of equation (1), which includes the log of *total* patent filings and the share of green patents in total patent filings.

To address potential endogeneity concerns, the SDN also conducts an instrumental variables exercise, where green patents in country *i* are instrumented with global green patent filings (that is, the sum of all filings in year *t* excluding country *i).* The instrument is strong, and valid reporting F-stat for first stage is consistently above 10 across a range of exercises considering either one instrument (filings in rest of the world) or two instruments (rest of the world filings and their lag) and upon controlling for growth expectations.

Channels

To investigate the channels through which the flow of patents affects economic activity, equation (1) is estimated by replacing the dependent variable with (1) real investment per capita, (2) real investment in machinery per capita, (3) real investment in structures per capita, and (4) total factor productivity. The variables pertaining to aggregate and disaggregate measures of investment as well as total factor productivity are obtained from the Penn World Tables (Version 10.1).

Comparison with the ICT Revolution

To benchmark the green transition to previous major technological breakthroughs, the baseline specification in (1) is applied for patents in information, communications, and technology (ICT) whereby ICT patents are identified using the new taxonomy flagging ICT patents provided by Inaba and Squicciarini (2017).[8] The specification is then expanded by interacting the independent variable of interest (the log of patent flow) with a dummy taking value one if the year falls during the ICT revolution period (1995–2005). The estimated equation is as follows:

$$\log Y_{i,t+h} - \log Y_{i,t-1} = \alpha + \beta_h \ \log P_{i,t}^{ICT} + \gamma_h \ \log P_{i,t}^{ICT} * ICT_{period} + \sum_{k=1}^{3} \lambda_{t-k}\, logP_{i,t-k}^{ICT} + \sum_{k=2}^{3} \mu_{t-k}\, logY_{i,t-k} + \eta_i + \nu_t + \epsilon_{it} \qquad (2)$$

The remaining variables are defined similarly as before, where $Y_{i,t}$ is real economic activity, real investment (aggregate, structural, and machinery), or total factor productivity.

II.2. Economic Effects of Green Innovation—US Firm-Level Analysis

To estimate the economic effects of green innovation on firm-level performance, the SDN follows the methodology by Kogan and others (2017). The baseline analysis is conducted by estimating the following econometric specification:

$$\log Y_{i,t+h} - \log Y_{i,t} = \alpha + \beta_h^{g} \theta_{i,t}^{g} + \beta_h^{ng} \theta_{i,t}^{ng} + \gamma \theta_{I\setminus i,t} + \boldsymbol{\delta X_{it}} + \eta_I + \nu_t + \epsilon_{it} \qquad (3)$$

[7] The autoregressive distributed lag (ARDL) methodology is robust to endogeneity or omitted variables concerns or whether the underlying variables are I(0) or I(1) (Pesaran and Smith 1995; Pesaran 1997). The specification includes three lags in line with the rule of thumb proposed by Chudik, Pesaran, and Yang (2018).

[8] https://www.oecd-ilibrary.org/science-and-technology/ict-a-new-taxonomy-based-on-the-international-patent-classification_ab16c396-en.

where Y_{it} denotes real revenue, α is a constant, θ_{it}^{m} is the citation-weighted innovation output of type $m \in \{g, ng\}$, with g referring to green patents and ng referring to nongreen patents, weighted by the firm's book asset value, $\theta_{I\setminus i,t}$ is the citation-weighted innovation output of firm i's competitors in sector I, $\boldsymbol{X_{it}}$ is a set of controls including the log value of gross PPE, the log number of employees, and one lag of the dependent variable, η_I is an industry fixed effect, ν_t is a time fixed effect, and ϵ_{it} is the idiosyncratic error term. Standard errors are clustered by both firm and year. To ensure that outliers are not driving the results, all variables are winsorized at the 1% level using annual breakpoints. Finally, to facilitate comparison between the green and nongreen innovation measures, both variables are normalized to unit standard deviation.

The coefficients of interest are β_h^{g} and β_h^{ng}, which can be interpreted as the association between a one standard deviation increase in innovation output of type g and ng, respectively, at time *t*, and the change in the dependent variable by horizon h.

II.3. Empirical Analysis of the Effect of Climate Policies on Patents

To estimate the impact of climate policies on innovation, the SDN resorts to local projection methods to capture the dynamic effects of a one standard deviation change in the policy metric used at time *t* on the flow of patents over multiple horizons. The regression is conducted through the following specification:

$$\log P_{i,t+h}^{j} - \log P_{i,t-1}^{j} = \alpha + \beta_h \,\Delta\,\mathrm{Policy}_{i,t} + \sum_{k=2}^{3} \lambda_{t-k}\, P_{i,t-k}^{j} + \sum_{k=1}^{2} \mu_{t-k}\,\Delta\,\mathrm{Policy}_{i,t-k} + \ln(oil)_t + year + \eta_i + \epsilon_{it} \quad (4)$$

where *j* is either green or total patents. The dependent variable captures the percentage change in the flow of green or total patent filings in country i over horizon h. The main independent variable is the change in the policy metric considered, which is either the change in the stock of active policies provided by the Climate Policy Database or the change in the Environmental Policy Stringency Index provided by the OECD. The specification abstracts from year fixed effects and includes instead a linear time trend and oil prices. This choice is made for two reasons. First, given that countries implement environmental policies at similar timings, the inclusion of time fixed effects absorbs much of the variation. More important, in order to capture the role of global policies as well as domestic policies, it is necessary to include oil prices to proxy for global changes in the supply and demand for oil, which is a substitute for LCTs. In an extension, we estimate (4) and include a global climate policy control by constructing a distance-weighted climate policy variable.

To gauge the relative impact of climate policies on green patents, Annex III summarizes results of a modified version of (4), where the dependent variable is the share of green patents in total patents. This provides a quantitative assessment of the differential impact of climate policies across patent types. Further, Annex III also shows the impact of climate policies on green, gray, and dirty patents in the energy sector, where the classification of patents is from Dechezleprêtre, Ménière, and Mohnen (2017).
For sectoral-level analysis presented in Annex III, specification (4) is adapted to capture the effect of the change in sector-specific policies (obtained from the Climate Policy Database) on green patents filed to that respective sector. Green patent filings are associated with their sector of application using the mapping provided by Goldschlag, Lybbert, and Zolas (2020).

To study the role of global policy action, the specification in (4) is extended to include the change in global policies, which are constructed using the distance-weighted sum of all policies in the same year excluding the country itself (see David, Komatsuzaki, and Pienknagura 2022 for a similar strategy in the context of structural reforms).

To address endogeneity concerns, the SDN also conducts an instrumental variables exercise, where climate policies in country *i* are instrumented with the total number of climate disasters in the world, excluding those in country *i* in year *t.*

II.4. Empirical Analysis of the Effect of Climate Policies on LCT Imports

To estimate the impact of policies on LCT imports, the SDN estimates two local projections. The first uses log LCT imports and explores the impact of changes in each of the climate policies and LCT tariffs. More precisely, the specification takes the following form:

$$m_{i,t+h}^{LCT} - m_{i,t-1}^{LCT} = \alpha_i^h + \gamma_i^h * year + \beta^h \Delta CP_{i,t} + \delta^h \Delta\tau_{i,t} + \theta^h X_{i,t} + \gamma^{ih} year + \varepsilon_{i,t} \qquad (5)$$

where m is imports in logs, $\Delta CP_{i,t}$ is the change in the stock of climate policies, $\Delta\tau_{i,t}$ is the change in LCT tariffs, $X_{i,t}$ includes controls (two lags of GDP and LCT imports growth, two lags of $\Delta CP_{i,t}$ and of $\Delta\tau_{i,t}$), $\gamma^{ih} year$ is a country-specific linear time trend, and α_i^h is a country fixed effect.

A second specification tracks the log difference between imports and GDP, which is equivalent to estimating the percentage increase in the ratio of the two variables in the aftermath of shocks. The specification mimics (5) but changes the dependent variable accordingly. To facilitate comparison, all charts in the main text plot the impact of a one standard deviation shock to the policy variable of interest.

II.5. Empirical Analysis of the Effect of Climate Policies on Bilateral FDI Flows

To gauge the impact of climate policies on FDI flows, the SDN follows Pienknagura (forthcoming) and estimates the following baseline equations. First it assesses the impact on aggregate FDI flows as a share of GDP by means of the following regression:

$$\frac{FDI^{\,j}}{GDP}_{c,t} = \alpha_c + \mu_t + \beta cp_{d,t-1} + \rho X_{c,t-1} + \varepsilon_{c,t} \qquad (6)$$

where *j* can be green, nongreen, or total greenfield FDI or net aggregate FDI, α_c is a country fixed effect, μ_t is a time fixed effect, $cp_{c,t-1}$ is the log of the CPD stock of climate policies in country *c* at time *t-1* (it also uses the EPS index as robustness), and $X_{c,t-1}$ includes additional controls (trade over GDP, GDP growth, GDP per capita, and capital per worker).

To study the impact of domestic and foreign climate policies, the SDN estimates the following equation using the Poisson-Pseudo Maximum Likelihood estimator proposed by Santos-Silva and Tenreyro (2006):

$$Y_{d,o,t}^{green} = \exp\{\alpha_d + \mu_{o,t} + \beta cp_{d,t} + \rho X_{d,t} + \sigma Z_{d,o,t}\} + \varepsilon_{d,o,t} \qquad (7)$$

where Y is either the number of green projects or the total dollar amount of the green projects, α_d are destination country fixed effects, $\mu_{o,t}$ are origin country-time fixed effects (in some extensions, only origin fixed effects are included to allow for the inclusion of origin country CPs), $cp_{d,t}$ is the log of the total number of active climate policies in the destination country, $X_{d,t}$ are destination-country-specific variables (GDP, population, tariffs), and $Z_{d,o,t}$ are country-pair variables (some time varying) such as distance, common language, and a trade agreement dummy.

The baseline bilateral specification is extended along two dimensions. First, (7) is expanded to explore whether the impact of CPs vary depending on the income level of the recipient. The modified equation is now:

$$Y_{d,o,t}^{green} = \exp\{\alpha_d + \mu_{o,t} + \beta^{AE} cp_{d,t}\mathbf{1}(\mathrm{d} \in \mathrm{AE}) + \beta^{EMDE} cp_{d,t}\mathbf{1}(\mathrm{d} \in \mathrm{EMDE}) + \rho X_{d,t} + \sigma Z_{d,o,t}\} + \varepsilon_{d,o,t} \quad (8)$$

where $\mathbf{1}(\mathrm{d} \in \mathrm{AE})$ is an indicator function. Second, the baseline regression is expanded to study the role of the composition of both destination and source countries' climate portfolios as follows:

$$Y_{d,o,t}^{green} = \exp\left\{\alpha_d + \mu_{o,t} + \beta cp_{d,t} + \sum_p \beta^{p,d} share_{d,p,t} + \rho X_{d,t} + \sigma Z_{d,o,t}\right\} + \varepsilon_{d,o,t} \qquad (9\mathrm{A})$$

$$Y_{d,o,t}^{green} = \exp\left\{\alpha_{d,t} + \mu_o + \beta cp_{o,t} + \sum_p \beta^{p,o} share_{o,p,t} + \rho X_{d,t} + \sigma Z_{d,o,t}\right\} + \varepsilon_{d,o,t} \qquad (9\mathrm{B})$$

where $share_{d,\mathrm{p},t}$ is share of policies of type p in country d's overall stock of climate policies. The estimated coefficients of 9A and 9B allow to compute the effect of different policy types in a way that is consistent with (7).

Annex III. Additional Results

This annex summarizes additional evidence cited in the main text of the SDN, presented in Table III.1. In particular, it focuses on extensions to the main analysis and robustness exercises. The summary table is divided into two categories: (1) economic impact of patents and (2) impact of climate policies on green patents and LCT trade.

Table III.1. Robustness Exercise and Extensions

1. Exercise Description	2. Additional Details	3. Comparison to Baseline/Main Result
Panel 1. Economic Impact of Patents at the Country and Firm Levels		
Differential impact of green patents and nongreen patents on energy intensive and trade exposed (EITE) sectors.	EITE sectors are classified according to Chateau, Jaumotte, and Schwerhoff (2022).	As is true of aggregate results, green patents have a similar effect compared to nongreen patent filings.
Differential impact of patents on different types of investment.	Break investment into structures and machinery.	Green patents have a larger and more significant effect on machinery investment in the short term and investment in structure in the short and medium term compared to nongreen.
Controlling for potential correlation between green and nongreen patents by considering total patents as main regressor and controlling for the green share.	Green share computed as the share of flow in green patent filings/flow in total filings.	No statistically significant impact of green share, suggesting no statistically significant difference in the impact of green patents relative to nongreen.
Inclusion of additional controls.	Controlling for growth expectations and changes in climate policies.	Increase or no change in point estimate compared to baseline. Green estimates remain statistically significant and not statistically different from nongreen estimates. Upon controlling for climate policies, the point estimate of green patent filings almost doubles.
Instrumental variables exercise.	Green patent filings instrumented with global patent filings excluding own filings.	Positive and statistically significant impact of patents on activity. Point estimates increase up to four times.
Firm-level impacts of patents on firm-level TFP and gross capital stock.	Analysis using US publicly traded firms.	Positive impact of green patents on TFP and the capital stock; effects are smaller compared to nongreen patents.
Panel 2. Impact of Climate Policies on Patent Filings and LCT trade		
Impact of changes in the climate policy count on the *share* of green patent filings in total patent fillings.	The breakdown of patents into gray and dirty for the energy sector is from Dechezleprêtre, Ménière, and Mohnen (2017).	Change in policies increases the share of green patent filings in total filings. A look at the electricity sector shows that an increase in climate policies increases the share of green and gray electricity patents in total electricity patents, while the share of dirty patents decreases over time.
Impact of EPS subcomponents on green patents	Studies the impact of the EPS subcomponents, breaking the technological support component into R&D subsidies and FITs.	Positive impact of FITs on green patents over the medium term
Instrumental variables exercise.	Climate policies instrumented with the number of total climate disasters in the rest of the world, in the spirit of Battarelli and others (2023), although the focus in that work is on global floods interacted with countries' coastline length.	Positive and statistically significant impact of policies on green patents.
Heterogenous impact of climate policies on LCT imports	Study the impact of revenue, expenditure, and neutral measures on LCT imports.	Positive and statistically significant impact of revenue and expenditure measures, nonsignificant impact of regulations, and negative effect of neutral, nonbinding measures.
Note: For details see Hasna and others (forthcoming a), Hasna and others (forthcoming b), Pienknagura (forthcoming a), and Pienknagura (forthcoming, b)		

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