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Ph.D. Dissertation of Sevde Arpaci Ayhan

Essays on Economic and Green Innovation

- Roles of Foreign Aid, R&D, and Environmental Policies -

경제 및 녹색 혁신에 대한 에세이: 공적개발원조, 연구개발 및 환경 정책의 역할

February 2023

Graduate School of International Studies
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International Studies Major

Sevde Arpaci Ayhan

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- Roles of Foreign Aid, R&D, and Environmental Policies -

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Abstract

Essays on Economic and Green Innovation:
Roles of Foreign Aid, R&D, and Environmental Policies

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This dissertation aims to understand the roles of various factors which affect the economic complexity and green innovation. It consists of three empirical essays. The first chapter focuses on foreign aid as it is one of the largest capital flows to developing countries. The second chapter compares R&D spending with patents as they are two common measurements of the innovative activity. The third chapter studies the institutional determinants of environment-friendly patents as there are an urgent need for the clean technologies.

The first essay investigates the impact of foreign aid on recipients' productive capabilities. Panel dataset consists of 86 countries covering the period 2003-2019. The novelty of this study is in linking aid to a new proxy for measuring productive capabilities called the Economic Complexity Index. Because of its ability to predict future growth, economic complexity is valuable in gauging aid effectiveness. The findings show that foreign aid benefits the recipients' economic complexity, although the results are mixed for the sectoral aid. Trade openness and foreign direct investment are additional factors affecting economic complexity in developing countries.

The second essay compares the effects of R&D expenditure and patents on the Economic Complexity Index. Panel dataset consists of 102 countries from 1996

to 2017. It contributes to the discussion about which innovation measurement could be a better proxy. The positive effect of R&D on economic complexity is remarkably robust to alternative models as well as estimations with sub-samples. Compared to R&D, the impact of patents is smaller and less robust across models. In the case of economic complexity which represents embedded knowledge and skills, R&D with its ability to generate new knowledge would be a better indicator than patents because the latter shows tangible outcomes rather than tacit knowledge accumulation.

The third essay estimates the impact of environmental policies on environment- friendly patents. This study contributes to the literature by incorporating the institutional quality into the analysis of green innovation. Panel data covers 31 countries from 1990 to 2019. Due to the count nature of patent data the model has a Poisson distribution. I use a pre-sample mean estimator to control for country fixed effects and to deal with heterogeneity among countries. While increased oil and electricity prices do not necessarily cause more green innovation at the country-level, environmental taxes support induced innovation hypothesis and increase green innovation. In line with scholars who emphasize the necessity of government intervention to tackle climate change, countries with more stringent policies, and bureaucratic quality perform better innovative activity in environment-friendly technologies. Finally, the causality between environmental policies and patents is confirmed with the use of control function approach and instrumental variable.

Keywords: Economic Complexity, Green Innovation, Foreign Aid, R&D, Patents, Environmental Policies
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Chapter I

Foreign Aid as a Catalyst for Improving Productive Capabilities in Recipients[2]

1.1. Introduction

Achieving structural transformation in developing countries is an essential step for growth. The transition from low to complex productivity requires increased capabilities. When these capabilities are embedded in a society, growth becomes sustainable. Because countries export what they produce, their export baskets are representative of their productive capabilities. The export of complex products leads to growth (Hausmann et al., 2007), especially through human capital accumulation (Ferrarini and Scaramozzino, 2013). For instance, Rodrik (2014) argues that rather than simply enhancing the export volume, a sophisticated export basket is an important determinant of China's rapid growth. In a similar vein, Felipe (2010) shows empirical evidence from East and Southeast Asian countries indicating that changes in their productivity structure towards sophistication result in the

[2] This chapter is published in the *Journal of International Development*, 2022.

acceleration of growth. However, resource dependency, the lack of capital, and limited knowhow are among the obstacles to more complex production. Most developing countries are primarily involved in raw and extractive industries.

Scholars have broadly studied how countries can diversify their production (Lashitew et al., 2021), and thereby exports. They find various diversifying factors in developing countries, including foreign aid, (among many, two prominent examples are Kamguia et al. (2022) and Gnangnon (2021)). Kamguia et al. (2022) claim that foreign aid is the third largest capital flow to developing countries, after foreign direct investment (FDI) and remittances. Studies on the determinants of productive structure use variants of diversity/concentration indices such as the Herfindahl-Hirschman Index (HHI), the entropy index, and the fitness index. However, the measurement of productive structure is much more complex than just assessing the diversity of production. The recent emergence of economic complexity measurements enables us to more precisely quantify a country's productive capabilities.

Because the concept of economic complexity is a recent phenomenon, studies on it are limited. This article is thus on the frontier of work studying the link between foreign aid and the recipient's economic complexity. The argument for this article is built on two strands of literature: economic complexity-related studies and work on the aid-diversification nexus. First, economic complexity has attracted scholars' interest in macroeconomic studies. The ability of economic complexity to predict future growth has made its application relevant to topics in development economics ranging from income growth to the environment. Scholars have demonstrated that economic complexity contributes significantly to economic growth (Hidalgo and Hausmann, 2009; Hausmann et al., 2013; Gala et al., 2016;

Sweet and Eterovic, 2019); income equality (Hartmann et al., 2017); export competitiveness (Olasehinde-Williams and Oshodi, 2021); human development (Ferraz et al., 2018); jobs and employment (Adam et al., 2019); and better environmental performance (Lapatinas et al., 2019; Neagu, 2019; Lapatinas et al., 2021; Romero and Gramkow, 2021). However, the determinants of economic complexity are less frequently studied than its contributions (see e.g. Bahar et al. (2020) for demographic determinants; Antonietti and Franco (2021), Nguyen and Su (2021) and Kamguia et al. (2022) for financial determinants; and Sweet and Eterovic Maggio (2015) for institutional determinants).

Second, to establish a link between aid and economic complexity, I revisit the question of aid effectiveness on recipients' trade characteristics (i.e. export diversity, sophistication, and upgrading). Scholars claim that aid for trade improves export diversity and quality (Cali and Velde, 2011; Gnangnon and Roberts, 2017; Gnangnon, 2019; Kim, 2019) as well as trade policy liberalization (Gnangnon, 2018). On the other hand, Munemo (2011) finds mixed results that while lower amount of foreign aid contributes to export diversification, higher amount of foreign aid impedes the diversification efforts.

In this article, I specifically aim to investigate whether foreign aid improves recipients' productive capabilities, measured by the economic complexity index (ECI). I argue that aid can become a catalyst for structural transformation: moving away from raw materials and extractive industries towards sophisticated sectors. Given the fact that ECI is measured by using a country's export data, understanding the ways in which foreign aid affects recipients' trade characteristics sheds light on how it also influences their productive capabilities. In addition to total aid, I use disaggregated aid data to determine the detailed impact of aid by sector (aid for

production sectors). Aid, as a capital flow, can impact productive capabilities indirectly through accumulating human capital, building infrastructure, and improving institutions. In addition, sectoral aid can directly target trade capabilities. For facilitating recipients' economic complexity, tacit knowledge transfer through technical assistance and indirect effects of capital building are how I expect aid to contribute. As an example to the knowledge transfer, Brenton and Uexkull (2009) show that the product-specific technical assistance leads to stronger export of the product.

The main contribution of this article is twofold. First, it applies ECI as a proxy for productive capabilities and reveals the determinants of ECI in aid-recipient countries. Second, it supports the 'bright side' of aid by presenting a strong, and consistent correlation between aid and ECI. Aid has a role in increasing productive capabilities, making recipients' export baskets more sophisticated. These findings are robust to controlling for a variety of factors that are used to explain determinants of diversification such as human capital, trade, FDI, and natural resources. The overall impact of aid is visible in the full sample and across all models, whereas the findings on the influence of sectoral aid is mixed. These results have both similarities to and differences from previous studies. Kamguia et al. (2022) find a negative impact of aid on economic complexity but report mix results for sectoral aid. Gnangnon (2021) shows a positive impact of aid for trade on economic complexity but a negative impact for other sectoral aid. The range of findings reported derives from the use of various aid data sources, variation in the set of controls variables included, and the selection of different time periods for the analysis.

The rest of the article is organized as follows. Section 2 provides a theoretical discussion on the connection between foreign aid and economic

complexity. Section 3 describes the variables, data sources, and empirical models. Section 4 presents the findings regarding the effects of aid and other factors on economic complexity. Section 5 concludes with a discussion of the findings, policy implications, and suggestions for further research.

1.2. Linking Foreign Aid and Economic Complexity

Countries with limited capacity to upgrade their exports need support to achieve structural transformation. A country's productive capabilities can be improved through learning and through the transfer of technical knowhow and skills. Foreign aid becomes a potential channel for capacity building, diffusion of information, and skill transfer. In this way, scholars show aid among the determinants of export diversification (Gnangnon, 2019; Munemo, 2011; Fonchamnyo and Akame, 2017; Ouedraogo et al., 2018).

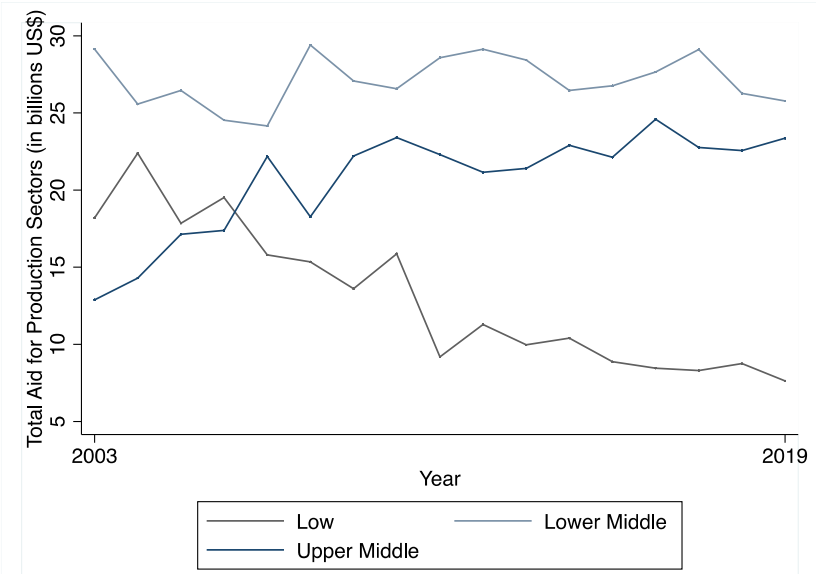
There is no consensus among scholars on the impact of foreign aid on trade and diversification. Although some scholars find a negative effect, with aid inducing real exchange rate overvaluation and the loss of export competitiveness (Osakwe, 2007; Rajan and Subramanian, 2005, 2011; van Wijnbergen, 1985; Kamguia et al., 2022), others show a positive contribution of aid to export diversification (Ouedraogo et al., 2018; Munemo, 2011; Fonchamnyo and Akame, 2017). There is a need to disaggregate aid data to investigate its detailed impact because the timing of aid (short-term vs long-term effects) results in different outcomes (Clemens et al., 2012). Such disaggregation also helps to better differentiate the effects of tacit knowledge and capital transfer by looking at sectoral aid.

In addition to the total aid, this study also measures the impact of sectoral aid. Aid for trade has gained momentum as a means of supporting structural

transformation and industrial diversification in recipient countries. Discussions on the effectiveness of aid for trade[3] are mostly positive, in contrast to the effects of total aid. Thus, I expect sectoral aid to also be effective in increasing productive capabilities. However, this study focuses on aid for production sectors instead of aid for trade. According to the Organization for Economic Co-operation and Development (OECD) Credit Reporting System (CRS), aid for trade captures trade policies and regulations that would not be sufficient to enhance recipients' productive capabilities. Aid for production sectors (with the OECD sector-classification code of 300) includes support for agriculture, industry, tourism, and trade policy, which better fit in the definition and scope of economic complexity. Unlike the increasing trend on aid for trade, aid for production sectors exhibits mixed trends among aid recipients. Figure 1.1 shows the total amount of aid allocated to production sectors by income level of aid recipients. As shown in the figure, the amount is steady for lower-middle-income countries, slightly increasing for upper-middle-income countries, and decreasing for low-income countries.

[3] To name a few of these findings: aid for trade is reported to promote exports (Bearce et al., 2013; Vijil, 2014); policy liberalization (Gnangnon, 2018), quality of exports (Wang and Xu, 2018), diversification (Gnangnon and Roberts, 2017; Hühne et al., 2014; Gnangnon, 2019; Kim, 2019), enhanced trade and welfare (Berrittella and Zhang, 2014), and reduced trading cost (Cali and Velde, 2011).

Figure 1.1. Disbursed Sectoral Aid by Income Level of Recipients.

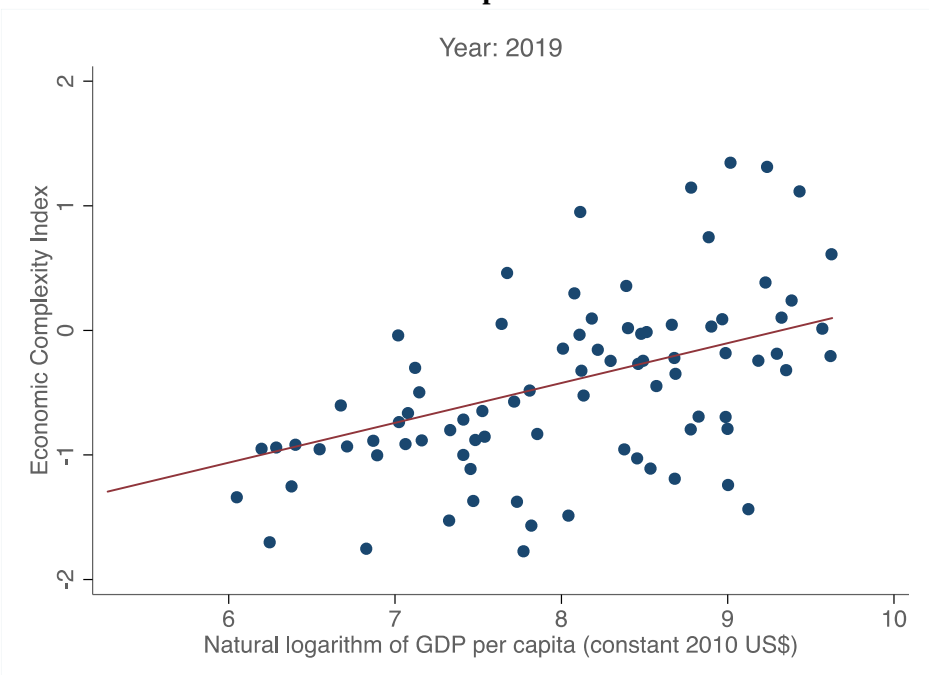


Source: Author

As discussed above, scholars have analysed the effects of foreign aid on various trade characteristics. In this article, I apply ECI as a proxy for productive capability. I prefer to use ECI over traditional measurements because it takes into account the sophistication of each product and extends our understanding of recipients' industrial structure. Hidalgo and Hausmann (2009) claim that ECI outperforms other indicators such as HHI and entropy measures. As mentioned above, ECI is not a simple proxy for a country's trade characteristics. It is also not about 'export-oriented growth', 'openness', 'diversification', or 'country size' (Hausmann et al., 2013). The intuition behind ECI is that sophisticated economies embody a high level of productive knowledge because each product reflects knowhow and skills (Figure 1.2). Countries that export various products also have higher productivity (Feenstra and Kee, 2004). ECI exploits a country's productive output, which incorporates embedded knowledge and skills. I compare the relationship between ECI and other measurements of productive structures in Figure

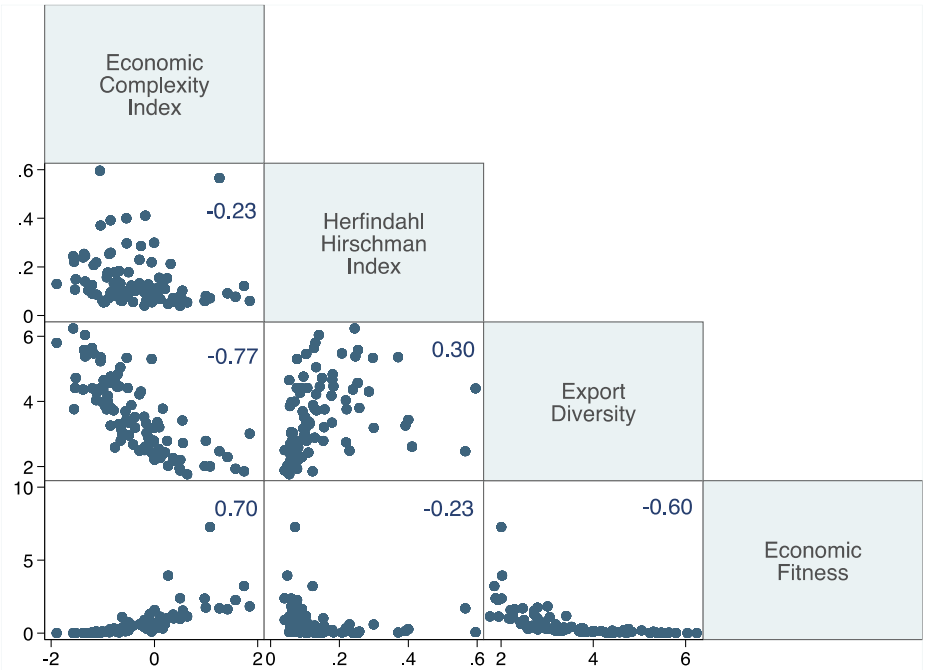
1.3. The matrix displays both correlation coefficients and scatterplots for each pair of variables. ECI is strongly correlated with the other measures. Thus, I link the foreign aid to ECI because aid can improve other traditional measurements of productive structure, as discussed above.

Figure 1.2. Bivariate Relation between ECI and GDP per Capita for Recipients



Source: Author

Figure 1.3. Correlation Matrix between ECI and Other Measurements for Productive Structure.



Source: Author

1.3. Data and Methodology

1.3.1. Data

This article investigates foreign aid's impact on economic complexity by constructing a panel dataset covering 86 countries from 2003 to 2019. Time frame and country choices are dependent on the data availability. The list of countries and summary statistics of the variables used in the empirical analysis can be found in the Appendix (Tables A1.1 and A1.2).

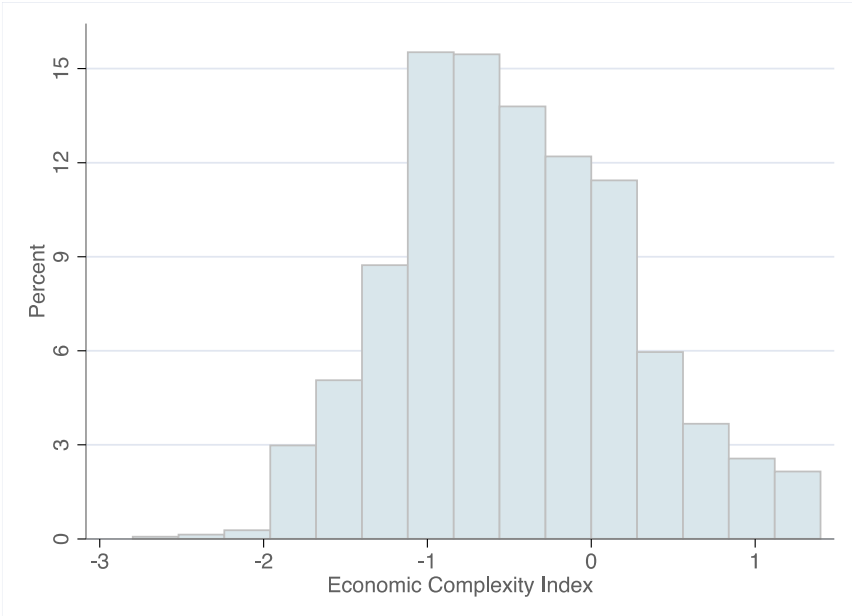
Economic complexity index as the dependent variable

ECI is available from two sources[4]. This study uses data downloaded from the Atlas of Economic Complexity Dataverse (2019). ECI assesses the complexity of a country's productive structure by its trade data using revealed comparative advantage. ECI ranges from -2.7989 (indicating a 'less complex economy') to +2.8626 (indicating a 'more complex economy')[5]. It depicts a country's production in terms of 'diversity' and 'ubiquity' (Hausmann et al., 2013). Diversity represents the number of different goods and services traded; ubiquity represents the commonness of those products. For instance, country A's export basket consists of five machinery products, which are not commonly produced by other countries, making country A's ECI high. In contrast, country B's export basket includes only one product, a raw food that can be produced by many countries, making country B's ECI low. Figure 1.4 shows a histogram for ECI. Among aid-recipient countries, ECI is above zero for only about 25%. Most of recipients produce relatively few and simple products.

[4] 'The Observatory of Economic Complexity' is available at https://oec.world/en. 'The Atlas of Economic Complexity' is available at https://atlas.cid.harvard.edu.

[5] This range holds for all countries. However, this study includes only aid recipients. Thus, the maximum ECI of the sample differs from that of all countries (see the summary statistics in Table A2).

Figure 1.4. Histogram of ECI.



Source: Author

Foreign aid as the main variable of interest

Data for the main variable of interest, foreign aid, are from OECD Statistics' CRS. I use disbursements instead of commitments because disbursements document aid that has already been spent on recipients. I divide aid into two categories to use in various models. First, aid disbursements of all types, for all sectors and from all donors is referred to as 'total aid' in this study. Second, sectoral aid disbursements for production sectors.

Control variables

To choose appropriate control variables[6], I considered the two abovementioned bodies of literature on economic complexity and the aid-trade nexus. First of all,

[6] Data on all control variables were obtained from World Development Indicators (WDI), available at https://databank.worldbank.org/source/world-development-indicators.

GDP is highly representative of a country's level of economic complexity (Hausmann et al., 2013; Hidalgo and Hausmann, 2009). It is also a measure of the size of a country's economy. Almost all studies on aid effectiveness - both mainstream and sectoral - include GDP per capita as a control variable.

Human capital can indicate the level of knowledge and skills embedded in a society. Zhu and Fu (2013) claim that education is a source of indigenous innovation that leads to export upgrade. Various measurements of schooling are used as proxies for a country's human capital level. However, including higher education level of a country as a control variable would decrease the number of observations in the present sample because limited data on tertiary school enrollment are available for developing countries. Rather, this article follows the literature on the determinants of ECI and use population to represent human capital (Sweet and Eterovic Maggio, 2015; Gnangnon, 2021; Kamguia et al., 2022).

Liberalization (Nguyen, 2016) and integration with global organizations are pathways to improve trade and upgrade exports, ultimately creating economic growth. Indeed, Anand et al. (2012) find that sophistication has a greater impact on growth in contexts with liberalized macroeconomic policy. I therefore include trade openness, which is measured as the sum of imports and exports as a share of GDP. Resource-abundant countries can be rich despite having undiversified production (Hausmann et al., 2013). Scholars show an inverse relationship between natural resources and economic complexity (Camargo and Gala, 2017; Alsharif et al., 2017). Including natural resource rent as a control variable captures possible "resource curse" effects.

Finally, FDI is another flow of capital to developing countries that is important for knowledge and technology diffusion. FDI is found to have positive

impacts in export diversification (Tadesse and Shukralla, 2011; Gnangnon and Roberts, 2017) and export upgrading (Amighini and Sanfilippo, 2014; Zhu and Fu, 2013; Harding and Javorcik, 2012), as well as in economic complexity (Antonietti and Franco, 2021). In this study, I focus on the knowledge transfer created by both FDI inflow and FDI outflow. I also expect a learning effect to occur from investing abroad through FDI outflow. Outward investment brings opportunities to enter new markets and open doors for access to foreign technology at reduced cost (World Bank, 2018). Therefore, controlling for both FDI inflow and outflow allows me to show the true impact of aid on economic complexity.

1.3.2. Empirical Model

I analyze the impact of foreign aid and other capital flows on the economic complexity of recipients. I investigate this question by estimating variants of the following baseline model:

$$\begin{aligned} ECI_{it} = \beta_0 + \beta_a aid_{t-1} + \beta_f FDI_{it} + \beta_g lnGDPpc_{it} + \beta_t trade_{it} \\ + \beta_r resource_{it} + \beta_p population_{it} + \beta_{tr}\text{Time}_t + \mu_i \\ + \varepsilon_{it} \end{aligned} \tag{1.1}$$

where i represents country and t represents time. I include country-fixed effects (μ_i) to capture time-invariant country-specific factors. ε_{it} is a stochastic error term, and β_0 is a constant. Time_t corresponds to time trend and is included to capture time effects within the examined period. Here, aid is the total aid received from all donors in all types of sectors as a percentage of GDP. I lag aid by one year because its impact may not be visible in the year it is received. I also use this model

to see the impact of sectoral aid by replacing the total aid variable with aid for production sectors and repeating the analysis.

As a robustness check, I also alternate the following three options for Equation 1.1. First, given that recipient countries have different characteristics at different development levels, I applied all models to subsamples of low-income, lower-middle-income, and upper-middle-income countries[7]. Second, I replaced FDI outflow with FDI inflow. Third, I substituted total aid data from the OECD CRS with bilateral and net official aid from the World Development Indicators (WDI)[8].

1.3.3. Identification Strategy

When estimating causal effects, econometric problems may lead to biased results. Omitted variables among the explanatory factors, simultaneous causality between the dependent and main predictor variable, and measurement errors are examples of such problems. Here, the aid variable could be correlated with the error term, and the direction of causality between aid and economic complexity might not be obvious. For instance, high economic complexity is usually associated with a high level of GDP, which would decrease the aid amount provided.

I follow the broad literature on the aid-growth and aid-trade nexuses to achieve identification of the models. The mainstream literature on aid effectiveness

[7] I followed the income level classification provided by the World Bank. Information is available at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

[8] There are two types of aid disbursements in WDI: i) net bilateral aid flows from Development Assistance Committee donors and ii) net official development assistance and official aid flows from all donors. Hereafter, the former is referred to as bilateral aid, and the latter is referred to as net official aid.

(e.g. Rajan and Subramanian (2008)) uses external instruments like colonial history, whereas the literature on aid and trade diversity (e.g. Hai (2021)) also applies GMM estimators. In this study, I use both techniques.

First, the dynamic panel model includes a lagged dependent variable on the right-hand side of the equation. However, the lagged dependent variable and the error term may be correlated. GMM estimator allows us to tackle endogeneity despite including the lagged dependent variable as a regressor. Here, I employ the system GMM estimator, which uses lagged differences of the endogenous variable as internal instruments (Blundell and Bond, 1998). System GMM is more efficient than difference GMM, as the former allows the use of more instruments with a large cross-sectional panel (Roodman, 2009). In the 'Results' section, I assess my choice of the two-step system GMM estimator by presenting diagnostic tests for i) the absence of the first-order serial correlation (AR(1)) in first differences and the second-order serial correlation (AR(2)) in the error term, and ii) the p-value for the Hansen test for over-identification. As a rule of thumb, I also present the number of instruments used in the model to ensure that there are fewer instruments than countries. The reduced-form equation is as follows:

$$\begin{aligned} ECI_{it} = \beta_0 + \beta_{ec} ECI_{it-1} + \beta_a aid_{it-1} + \beta_f FDI_{it} + \beta_g lnGDPpc_{it} \\ + \beta_t trade_{it} + \beta_r resource_{it} + \beta_p population_{it} \\ + \beta_{tr} \mathrm{Time}_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{1.2}$$

Second, I apply the two-stage least squares (2SLS) instrumental variable technique. Finding a strong, time-varying instrument for regression including country fixed effects, that also meets the exclusion restriction conditions, is not easy.

Some previous work (i.e. Jones and Tarp (2016)) selects recipient-level instruments such as population, life expectancy, and a dummy for ever having been a colony. Instead of recipient-specific characteristics, I instrument aid on the supply-side. The variables of population and life expectancy are representative of human capital and thus economic complexity. A time-invariant dummy variables for colonial ties is also not a good fit for the panel setting because such variables are omitted at the first stage. Therefore, I follow Tavares (2003)[9] and construct an instrument based on donor-related characteristics, similar to Rajan and Subramanian (2008, 2011). Donors with greater historical ties tend to provide more aid.

Construction is based on the bilateral donor-recipient (j-i) relationship, including colonial history, common language, common religion, common border, and the inverse of bilateral geographical distance. These factors are multiplied by the bilateral aid flow from the top five donors[10] and aggregated up to calculate predicted aid, similar to the method used by Frankel and Romer (1999). The equation estimated in the first stage is as follows:

$$\begin{aligned} aid_{it} = \beta_0 + \beta_d \sum_{j=1}^{5} dist_{ij} * aid_{ijt} + \beta_c \sum_{j=1}^{5} colony_{ij} * aid_{ijt} \\ + \beta_l \sum_{j=1}^{5} comlang_{ij} * aid_{ijt} + \beta_r \sum_{j=1}^{5} comrelig_{ij} * aid_{ijt} \\ + \beta_b \sum_{j=1}^{5} combord_{ij} * aid_{ijt} + \eta_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{1.3}$$

[9] This instrumentation strategy is applied by other scholars (see Chauvet et al. (2019) and Kamguia et al. (2022))

[10] Germany, France, Japan, the United Kingdom, and the United States of America.

The predicted value of the aid from this regression is then used in the second-stage regression in the two-stage model. I present i) first stage F statistics for the relevance of the instruments and ii) statistics for an under-identification test for the quality of the instruments. Using GMM and 2SLS estimators in addition to the baseline OLS model provides justification for the identifying assumptions and robustness of the findings.

1.4. Results

Table 1.1. The Impact of Total Aid on ECI.

Depend. vr.: ECI	(1)	(2)	(3)	(4)
Sample	All	Low Income	Lower M. Inc.	Upper M. Inc.
Total Aid	0.003*	0.001	0.003	0.039
% of GDP	(0.001)	(0.001)	(0.004)	(0.060)
Trade	0.001*	0.001	0.002**	0.003*
% of GDP	(0.001)	(0.001)	(0.001)	(0.001)
GDP p capita	0.200	0.779**	0.099	0.323
in log.	(0.132)	(0.279)	(0.166)	(0.208)
Fdi Outflow	0.006**	0.003**	0.010	0.015**
% of GDP	(0.003)	(0.001)	(0.010)	(0.006)
Resources	-0.007**	0.011	-0.010***	-0.013***
% of GDP	(0.003)	(0.007)	(0.003)	(0.004)
Population	0.280	0.250	0.595	-0.128
in log.	(0.257)	(0.902)	(0.364)	(0.478)
Time Trend	-0.011	-0.028	-0.012	-0.008
	(0.007)	(0.027)	(0.011)	(0.011)
Constant	16.089	46.821	13.243	15.973
	(10.231)	(37.328)	(16.530)	(14.549)
Observations	1,277	256	509	484
R-squared	0.034	0.107	0.086	0.082
# of country	80	16	33	29
F statistics	0.0616	1.53e-07	0.000223	0.00421

Robust standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. OLS estimator with country fixed-effects is used in all models.

Table 1.1 presents results from the first model, measuring the effects of aggregated aid disbursements on ECI. Each column has a different sample size by the recipients' income level. Total aid has a positive and significant impact on economic complexity in the full sample: a one-unit increase in aid disbursement as a percentage of GDP brings a 0.3 % rise in ECI. Considering the range of ECI approximately from -2 to +2, this 0.3 % rise in ECI is meaningful. The effect of aid is no longer visible when the sample is divided by income level. Trade openness is another factor with a positive and significant impact in all samples except low-income countries. As the literature on trade liberalization (Agosin et al., 2012; Nguyen, 2016; Osakwe et al., 2018) suggests, openness to trade influences economic complexity.

GDP per capita is a determinant of economic complexity only in low-income countries, where a one-unit increase in the logarithm of GDP per capita leads to an approximately 80 % increase in ECI. Such a magnitude is not seen for countries with higher income levels. As countries climb the development ladder, diversification of their productive capabilities becomes more difficult.

Natural resource rent as a percentage of GDP has a consistent negative and significant result. Overall, a one-unit higher resource rent value results in a decrease in ECI of about 1 %. Resource dependency's role in preventing diversification (Osakwe, 2007) is reflected in these findings. Only in low-income countries is resource dependency not an obstacle to diversification. Finally, although FDI inflow is identified as an essential capital flow in the diversification-related literature, this study reveals a significant impact of FDI outflow on ECI. Especially in low- and upper-middle-income countries, FDI outflow has positive and significant results. In the full sample, a one unit increase in FDI outflow results in 0.6% rise in ECI.

Table 1.2. The Impact of Sectoral Aid on ECI.

Depend. vr.: ECI	(1)	(2)	(3)	(4)
Sample	All	Low Income	Lower M. Inc.	Upper M. Inc.
Sectoral Aid	0.022	-0.017	0.059	0.185
% of GDP	(0.080)	(0.113)	(0.080)	(0.126)
Trade	0.001	0.000	0.002**	0.003**
% of GDP	(0.001)	(0.001)	(0.001)	(0.001)
GDP p capita	0.195	0.787**	0.099	0.314
in log.	(0.133)	(0.290)	(0.167)	(0.208)
Fdi Outflow	0.005*	0.002***	0.009	0.015**
% of GDP	(0.003)	(0.001)	(0.010)	(0.006)
Resources	-0.006*	0.011	-0.010***	-0.013***
% of GDP	(0.003)	(0.007)	(0.003)	(0.004)
Population	0.254	0.271	0.604	-0.073
in log.	(0.254)	(0.884)	(0.367)	(0.467)
Time Trend	-0.011	-0.029	-0.013	-0.009
	(0.007)	(0.027)	(0.011)	(0.011)
Constant	15.930	48.171	13.910	15.512
	(10.244)	(39.167)	(16.464)	(14.143)
Observations	1,277	256	509	484
R-squared	0.032	0.106	0.086	0.080
# of country	80	16	33	29
F statistics p.	0.0148	1.16e-09	0.000577	0.00471

Robust standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. OLS estimator with country fixed-effects is used in all models. Sectoral aid refers to the aid given for production sectors.

The next model examines the impact of aid specifically given for the production sectors (Table 1.2). Here, sectoral aid seems to have no direct influence on economic complexity. It may be that the contribution of aid to economic complexity is driven by impacts in other sectors, such as economic and social infrastructure, rather than productive industries. All control variables parallel the results described for the first model, as expected, in terms of both magnitude and

significance. Overall, these results support Clemens et al.'s (2012) suggestion to evaluate aid effectiveness using disaggregated data.

1.4.1. Robustness Check

Consistent results across different models demonstrate that findings are robust. Here, I apply the models to subsamples with different income levels as a way of measuring robustness. In this section, I also estimate the baseline model with altered control variables and using data from different sources. All findings are provided in the Appendix (Tables A1.4-A1.6). First, I replace FDI outflow with FDI inflow. Like outward investment, FDI inflow positively affects economic complexity. However, its influence is not visible in the dynamic models. Second, bilateral and total net aid data from the WDI are substituted for the total aid variable from the OECD CRS. Both bilateral aid and total net aid are significant and effective in the dynamic models. The control variables are quite consistent with the baseline findings. In brief, trade, FDI outflow, and GDP per capita have significant positive effects, and natural resource rent has a significant negative effect.

1.4.2. Instrumenting the Foreign Aid

In this section, I present results from the GMM and 2SLS techniques to address the endogeneity of foreign aid in all baseline models. Adding a lagged dependent variable to the baseline model is a good fit because economic complexity is a predictor of a country's future complexity (Hidalgo and Hausmann, 2009). Table 1.3 illustrates the path-dependency in the evolution of economic complexity and shows that the previous year's ECI has a high impact in terms of both magnitude and significance. Coefficients of the aid variables gain efficiency in the full sample for

the dynamic models. The OLS estimates in Table 1.1 are therefore downward biased, a result that disregards the simultaneity between aid and economic complexity. This indicates attenuation bias: a measurement error in the regressor.

Moreover, aid for production sectors has significant effects in the dynamic models. All aid variables lose significance in the 2SLS estimations. One weakness of constructing an instrumental variable through the bilateral relationship with top five donors is the lack of data on disaggregated aid. Those donors do not necessarily provide sectoral aid every year to each recipient. Therefore, 2SLS estimations have fewer observations. Moving to the control variables, openness to trade and natural resource rents have consistent impacts across all models. GDP per capita and FDI outflow, in contrast, have inconsistent effects. Post-estimations results are also included in Table 1.3 to demonstrate the reliability of findings. Insignificant p-values for the Hansen tests indicate that over-identification restrictions cannot be rejected. A significant AR(1) test and insignificant AR(2) test show that the error term is not highly serially correlated. F-tests from the first stage for excluded instruments are large and above the conventional threshold of 10. The under-identification test shows that the external instruments are relevant. Overall, the tests results suggest that the instruments are valid, and the identification assumptions are hold.

Table 1.3. Instrumenting the Aid Variable through 2SLS and GMM Methods.

Dep.vr.: ECI	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	GMM	IV	OLS	GMM	IV
Lagged ECI	0.454***	0.416***		0.455***	0.548***	
	(0.044)	(0.103)		(0.043)	(0.097)	
Total Aid	0.006***	0.005**	0.006			
% of GDP	(0.002)	(0.003)	(0.004)			
Sectoral Aid				0.002	0.130*	-0.084
% of GDP				(0.042)	(0.070)	(0.121)
Trade	0.002***	0.003**	0.002***	0.001**	0.004***	0.002*
% of GDP	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP p. c.	0.157**	0.435**	0.016	0.144**	0.207***	0.424***
in log.	(0.066)	(0.198)	(0.054)	(0.067)	(0.049)	(0.071)
Resources	-0.007***	-0.019***	-0.009***	-0.006***	-0.018***	0.000
% of GDP	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.004)
Population	0.234	0.144**	0.018	0.161	0.034	-0.407**
in log.	(0.149)	(0.070)	(0.092)	(0.149)	(0.051)	(0.190)
Fdi Outflow	0.001	0.001	0.005**	-0.001	-0.001	0.004
% of GDP	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)
Observations	1,207	1,207	1,142	1,207	1,207	390
R-squared	0.272		0.054	0.263		0.109
# of country	80	80	77	80	80	48
Hansen p.		0.191			0.121	
AR(1) p.		0.000			0.000	
AR(2) p.		0.613			0.758	
# of Instr.		23			57	
First stage F			53.38			120.7
Underid. p.			0.00376			3.78e-05

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All columns include the full sample with country fixed-effects and time trends. Columns 1, 4, and 7 are OLS estimations for dynamic models as in Eq. 1.3. Columns 2, 5, and 8 use two-step System GMM estimators. Variables aid, trade, FDI, and GDP per capita are treated as endogenous, while natural resource, population and time trend are treated as exogenous. Maximum three lags of endogenous variables and lagged dependent variable are used as internal instruments. Columns 3, 6, and 9 use 2SLS estimators. External instrumental variables are constructed for each type of aid as in Eq 3. Sectoral Aid refers to the aid given for production sectors.

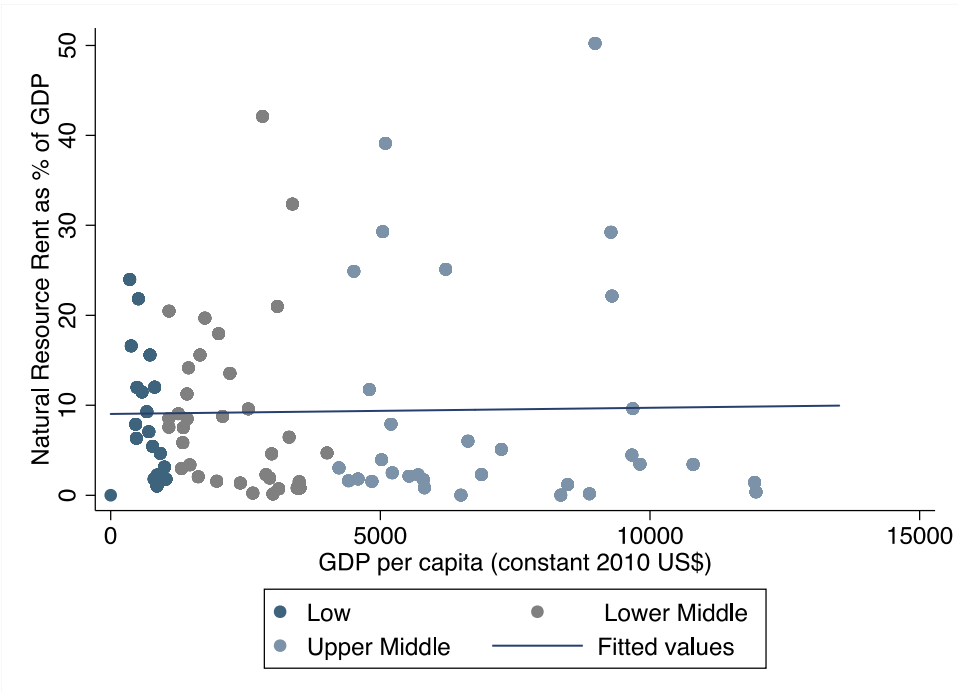
1.5. Concluding Remarks

This study has interesting findings, policy implications, and future research suggestions. First, the results support the "resource curse" theory (Sachs and Warner, 2001) by showing a significant negative impact on ECI across the examined models. Figure 1.5 shows that, for all levels of income, there are countries with low and high percentages of natural resource rents. There is one aspect of resource dependency to highlight in the findings - its relatively insignificant and low impact in low-income countries. Natural resource rent is not expected to be a big obstacle to diversification efforts in these countries, although productive capabilities are limited and concentrated on raw materials in low-income countries. One reason for this is that low-income countries have low resource rents – not exceeding 25% of GDP (Figure 5) - so the impact of resource dependency might not be visible. For policy makers, this finding means that concentration on raw materials, or resource dependency at the beginning of the development ladder may not impede the diversification efforts.

This study's finding on the catalysing role of aid in improving recipient countries' economic complexity represents both an additive contribution (Gnangnon, 2021) and a contrast (Kamguia et al., 2022) to existing literature. The different results may stem from differences in the choice of control variables, time periods, sample countries, and aid data sources across studies. For instance, Gnangnon's (2021) research focuses on aid for trade, while Kamguia et al.'s (2022) research uses WDI's net ODA and commitments, and this research uses aid disbursements (not including commitments) from OECD CRS. Moreover, authors build their research on different theoretical backgrounds. For instance, Kamguia et al. (2022) link aid with economic complexity through channels of institutions and human development. They argue that aid is associated with bad institutions and low

human development, so they expect to find a negative impact of aid on economic complexity. On contrary, this research considers the ability of aid to transfer knowledge and build infrastructure and capacity. Variation in theoretical background, data and methods results in mixed roles of aid, such as impeding or improving economic complexity under different conditions.

Figure 1.5. Bivariate Relation between Natural Resource Rent and GDP per Capita by Income Groups.



Source: Author

In addition to the significant role of aid, this study finds that FDI is effective for increasing economic complexity. Scholars commonly discuss the contribution of FDI inflow (e.g., Antonietti and Franco (2021)) but, in this study, FDI outflow is influential in terms of building productive capabilities. The positive relationship between FDI outflow and economic complexity can be studied further by including

all countries, rather than only aid recipients, to reveal the impact of this variable in advanced economies.

Furthermore, contrary to the literature that discusses the substantial effect of aid in low-income countries vs the attractiveness of FDI in middle-income countries (e.g. Kim (2018)), my findings show that FDI outflow and trade openness can be supportive in low-income countries, whereas aid is more effective in upper-middle-income countries. One reason for this may be that low-income countries need the transfer of knowhow, skills, and technology. Investing abroad and integration into the global economy can increase this kind of knowledge base. Therefore, low-income countries should seek opportunities to engage in international economic activities. As income level rises, aid may be a facilitator, building upon existing productive capabilities. Middle-income countries have relatively high skills, knowledge, and infrastructure to take advantage of the benefits of aid.

It should also be noted that the results in this study are limited to the time frame of 2003-2019 because of the lack of data on aid disbursements. Yet, countries who have achieved great sophistication in their production, such as South Korea, are not included in this period because they were no longer aid recipients. It would be useful to look at previous years to determine whether foreign aid of any type or in any sector affected such countries' diversification efforts. It would also be useful to conduct in-depth individual case studies for these countries. Additionally, when the full sample in this study is divided into subsamples of various income levels, the numbers of countries and observations undergo a shift in each model. Having a low vs high number of observations might also affect the significance of the coefficients. Thus, it is crucial to keep in mind the differences in the numbers of observations when comparing the results from disaggregated data.

In sum, this study illustrates a strong and robust correlation between foreign aid and productive capabilities in recipient countries. The findings suggest that recipients gain the ability to sophisticate their production through foreign aid. The study also highlights different attributes of recipient countries at different income levels in terms of utilizing from foreign aid – including its various types and modalities – while achieving the desired structural transformation.

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Appendix

Table A1.1. List of Countries.

Algeria	Cote de I'voire	Iran	Moldova	South Africa
Angola	Cuba	Jamaica	Mongolia	Sri Lanka
Argentina	Dem. Rep. of Congo	Jordan	Morocco	Tajikistan
Armenia	Dominican Republic	Kazakhstan	Mozambique	Tanzania
Azerbaijan	Ecuador	Kenya	Myanmar	Thailand
Bangladesh	Egypt	Kyrgyzstan	Namibia	Togo
Bolivia	El Salvador	Laos	Nicaragua	Tunisia
Botswana	Eswatini	Lebanon	Nigeria	Turkey
Brazil	Ethiopia	Liberia	N. Macedonia	Turkmenistan
Burkina Faso	Gabon	Libya	Pakistan	Uganda
Cambodia	Georgia	Madagascar	Panama	Ukraine
Cameroon	Ghana	Malawi	Papua	Uruguay
Chile	Guatemala	Malaysia	Paraguay	Uzbekistan
China	Guinea	Mali	Peru	Venezuela
Colombia	Honduras	Mauritania	Philippines	Vietnam
Congo	India	Mauritius	Senegal	Yemen
Costa Rica	Indonesia	Mexico	Serbia	Zambia
				Zimbabwe

Table A1.2. Summary Statistics.

VARIABLES	N	Mean	SD	Min	Max
ECI	1,443	-0.472	0.704	-2.799	1.400
FDI Outflow	1,364	0.956	3.911	-10.95	76.00
Trade	1,392	76.41	34.51	0.167	311.4
Population	1462	16.60	1.43	13.83	21.05
Resources	1,454	9.236	11.36	0.001	68.00
GDP p capita	1,456	7.856	0.981	5.272	9.628
Total Aid	1,450	3.763	6.677	0.009	87.28
Aid for Production	1,450	0.262	0.361	0	2.304

Table A1.3. Correlation Matrix.

	ECI	Total Aid	FDI Outflow	Trade	Pop.	GDP p cap.	Resource
ECI	1.000						
Total Aid	- 0.254	1.000					
FDI Outf.	0.001	0.098	1.000				
Trade	0.084	0.153	0.267	1.000			
Population	0.198	-0.153	-0.083	-0.454	1.000		
GDP p cap.	0.435	-0.545	-0.018	-0.033	-0.086	1.000	
Resources	-0.55	0.112	0.193	0.152	-0.062	-0.025	1.000

Table A1.4. The Impact of Total Aid with FDI Inflow as Control Variable.

Dependent vr.:	(1)	(2)	(3)	(4)
ECI	OLS	IV	OLS	GMM
Lagged ECI			0.439***	0.645***
			(0.044)	(0.175)
Total Aid	0.001	0.003	0.005***	0.016*
% of GDP	(0.002)	(0.003)	(0.002)	(0.008)
Trade	0.001**	0.002***	0.001***	0.002
% of GDP	(0.001)	(0.001)	(0.000)	(0.001)
GDP p capita	0.129	-0.011	0.081	0.394**
in log.	(0.111)	(0.047)	(0.067)	(0.197)
Fdi Inflow	0.004**	0.004***	0.001	0.006
% of GDP	(0.001)	(0.001)	(0.001)	(0.007)
Resources	-0.004	-0.007***	-0.005**	-0.013**
% of GDP	(0.003)	(0.002)	(0.002)	(0.006)
Population	0.248	0.057	0.196	0.101**
in log.	(0.249)	(0.090)	(0.146)	(0.039)
Observations	1,345	1,206	1,267	1,267
R-squared	0.031	0.054	0.246	
# of country	82	79	82	82
F statistics	0.0642		0	
First stage F		71.60		
Underiden. test p.		0.00256		
Hansen p.				0.566
AB test AR(1) p.				0.000
AB test AR(2) p.				0.903
# of Instruments				14

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All columns include the full sample with country fixed-effects and time trends. Column 1 is OLS estimation as in Eq. 1. Column 2 uses 2SLS estimator. External instrumental variable is constructed as in Eq. 4. Column 3 is OLS estimation for dynamic model as in Eq. 3. Columns 4 uses two-step System GMM estimator. Variables aid, trade, FDI, and GDP per capita are treated as endogenous, while resource rent, population and time trend are treated as exogenous. Maximum three lags of endogenous variables and lagged dependent variable are used as internal instruments.

Table A1.5. Bilateral Aid from World Development Indicators.

Dependent vr.:	(1)	(2)	(3)	(4)
ECI	OLS	IV	OLS	GMM
Lagged ECI			0.462***	0.530***
			(0.043)	(0.084)
Bilateral Aid	-0.000	0.001	0.006	0.012***
% of GDP	(0.003)	(0.007)	(0.005)	(0.004)
Trade	0.001	0.001	0.002***	0.004**
% of GDP	(0.001)	(0.001)	(0.000)	(0.002)
GDP p capita	0.259**	0.031	0.178***	0.218***
in log.	(0.129)	(0.054)	(0.062)	(0.044)
Fdi Outflow	0.005*	0.004*	-0.001	-0.002
% of GDP	(0.003)	(0.002)	(0.002)	(0.001)
Resources	-0.006*	-0.005*	-0.006***	-0.019***
% of GDP	(0.003)	(0.003)	(0.002)	(0.003)
Population	0.337	-0.028	0.214	0.067
in log.	(0.243)	(0.096)	(0.140)	(0.048)
Observations	1,283	1,208	1,211	1,211
R-squared	0.036	0.012	0.273	
# of country	80	78	80	80
F statistics	0.0205		0	
First stage F		302.4		
Underiden. test p.		0.00107		
Hansen p.				0.149
AB test AR(1) p.				0.000
AB test AR(2) p.				0.616
# of Instruments				57

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All columns include the full sample with country fixed-effects and time trends. Column 1 is OLS estimation as in Eq. 1. Column 2 uses 2SLS estimator. External instrumental variable is constructed as in Eq. 4. Column 3 is OLS estimation for dynamic model as in Eq. 3. Columns 4 uses two-step System GMM estimator. Variables aid, trade, FDI, and GDP per capita are treated as endogenous, while resource rent, population and time trend are treated as exogenous. Maximum three lags of endogenous variables and lagged dependent variable are used as internal instruments.

Table A1.6. Net Official Aid from World Development Indicators.

Dependent vr.:	(1)	(2)	(3)	(4)
ECI	OLS	IV	OLS	GMM
Lagged ECI			0.461***	0.530***
			(0.043)	(0.098)
Net Total Aid	0.002	0.008	0.006*	0.007**
% of GDP	(0.002)	(0.005)	(0.003)	(0.003)
Trade	0.001	0.002***	0.002***	0.003*
% of GDP	(0.001)	(0.001)	(0.000)	(0.002)
GDP p capita	0.266**	0.024	0.185***	0.197***
in log.	(0.128)	(0.055)	(0.061)	(0.051)
Fdi Outflow	0.005*	0.005**	0.000	-0.000
% of GDP	(0.003)	(0.002)	(0.002)	(0.002)
Resources	-0.006**	-0.009***	-0.006***	-0.019***
% of GDP	(0.003)	(0.002)	(0.002)	(0.004)
Population	0.353	0.012	0.238*	0.060
in log.	(0.244)	(0.091)	(0.140)	(0.053)
Observations	1,283	1,142	1,211	1,211
R-squared	0.037	0.053	0.277	
# of country	80	77	80	80
F statistics	0.0252		0	
First stage F		44.66		
Underiden. test p.		0.00275		
Hansen p.				0.123
AB test AR(1) p.				0.000
AB test AR(2) p.				0.611
# of Instruments				57

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All columns include the full sample with country fixed-effects and time trends. Column 1 is OLS estimation as in Eq. 1. Column 2 uses 2SLS estimator. External instrumental variable is constructed as in Eq. 4. Column 3 is OLS estimation for dynamic model as in Eq. 3. Columns 4 uses two-step System GMM estimator. Variables aid, trade, FDI, and GDP per capita are treated as endogenous, while resource rent, population and time trend are treated as exogenous. Maximum three lags of endogenous variables and lagged dependent variable are used as internal instruments.

Chapter II

Innovation Measures and Economic Complexity: Comparing R&D Expenditure with Patents

2.1. Introduction

The role of economic complexity in predicting future growth (Hausmann et al., 2013) builds on the Schumpeter growth model. The quality of exports explains the growth differences between countries (Hausmann et al., 2007). For instance, Rodrik (2006) claims that rather than simply increasing the export volume, a sophisticated export basket is behind the China's rapid growth. Schumpeterian (Schumpeter, 1942) and endogenous (Romer, 1994) growth models identify the innovation as a facilitator of growth that enabled latecomer countries to catch-up and even surpass the frontiers. It was the shortfall of the neoclassical growth model to explain differences in growth rates among frontiers and catch-up countries.

Economic complexity captures the innovation practiced in a country, whether the innovative capacity is embedded into the whole economy. Several scholars have considered the role of economic complexity in representing innovative capability and linked economic complexity with innovation related measures. Sweet and Eterovic (2015) found that stronger intellectual property rights (IPR) engender

higher levels of economic complexity, which in turn increases the total productivity growth (Sweet and Eterovic, 2019). In addition to the intellectual property rights, spending on research and development (R&D) and number of patents can be factors as the driver of economic complexity.

R&D is a significant input for innovative activity thanks to its capability to accumulate knowledge. Aghion and Howitt (1992) claim that future growth of an economy depends on economy-wide research. In a similar vein, Grossman and Helpman (1991) argue that each industry's success depends on the total R&D targeted to that product. R&D allows countries to move on to new industries, in which knowhow and skills are particularly required, by reducing their cost and risk (Mewes and Broekel, 2020). It also enhances the firms' absorptive capacity (Cohen and Levinthal, 1990).

Sustainable Development Goals (SDGs) Target 9.5 calls upon a substantial increase in research and development (R&D) spending and R&D workers[11]. In recent years, global spending on R&D reached a record of US $1.7 billion but still it does not exceed 5% of GDP for any country.[12] Around 70% of countries spend only less than 1% of their GDP on R&D (Figure 1). Two barriers that are visible on R&D spending that are lower income level (Goni and Maloney, 2017) and natural resource endowment (Kamguia et al., 2022).

However, there are disadvantages of the use of R&D as an innovation measurement. First, not all R&D spending targets for a tangible outcome, or

[11] Information is available at https://sdg.tracking-progress.org/indicator/9-5-1-research-and-development-expenditure-proportion-of-gdp/

[12] Information is available at http://uis.unesco.org/apps/visualisations/research-and-development-spending/

technological product. For instance, R&D, which is spent on the fields such as social sciences, might not contribute to economic complexity. Because the measurement of economic complexity basically relies on the number of actual products in a country's export basket. Second, the effectiveness of R&D cannot be measured simply by the total amount spent because the management[13] of R&D spending and the institutional environment are also important factors that affect the outcome (Coluccia et al., 2020). Next handicap is about the lack of data for small and medium level firms as well as low-income countries. For example, in their study on Netherlands, Brouwer and Kleinknecht (1997) reveal that R&D represented only one quarter of total product innovation expenditure. Similarly, UNESCO (2010) points out the fact that there is no standard data collection system especially among low-income countries.

Alternatively, patent data is also used as a proxy for innovation. Motivation behind the use of patents is being a tangible output. It shows the actual innovative outcome. Compared to R&D data, patents are popular indicator, accessible, replicable, and standardized. However, patent data also carries its own shortfalls. First, not every technology/product is patentable (Mansfield, 1986; Griliches, 1990). Thus, it partly reflects the innovative activities and research efforts. Second, patenting is too costly (Hall et al., 2013). Total amount of costs spent on patents in one year in the United States correspond to the one third of R&D spending[14]. Third,

[13] An example discussion on the importance of R&D management can be found via this link: https://www.forbes.com/sites/tendayiviki/2016/08/21/why-rd-spending-is-not-a-measure-of-innovation/?sh=213d2f91c77d

[14] Information is retrieved from the link: https://www.promarket.org/2021/03/19/patents-bad-measure-innovation-new-metric/

patents capture only explicit side of innovation rather than tacit knowledge accumulation (Nelson, 2005). Finally, not every country has a culture of patenting that also causes to home-bias in the specific patent offices such as the European Union (EU) patent office (Varsakelis, 2001).

Existing literature about the impact of innovation measurements on the sophistication of production is limited. I fill this gap by linking R&D and patents with the Economic Complexity Index (ECI), which measures diversity and ubiquity of an export basket. Diversity refers to the number of different products in an export basket, while ubiquity refers to commonness of those products (Hausmann et al., 2013). This study estimates the impacts of both R&D and patents on economic complexity using panel regressions for 102 countries from 1996 to 2017. Once I control for income level, trade openness, human capital, natural resources, and institutions, I find significant positive effects of R&D and patents across models. This finding is in line with endogenous growth theories that technology is an essential driver of innovative production, especially for developing countries to catch-up with frontiers. My contribution is in two streams of literature that are assessing the effectiveness of innovation measures and understanding the determinants of economic complexity. While higher R&D expenditure and number of patents lead to sophisticated production and exports, the influence of R&D is larger and more robust than patents.

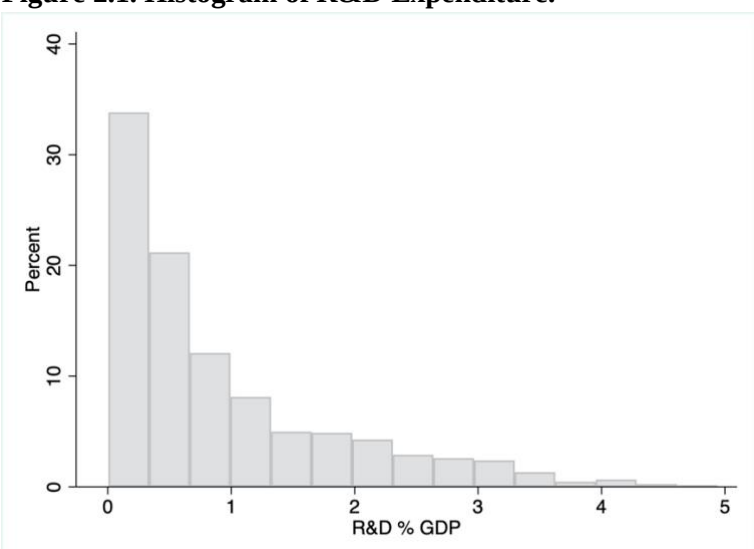
The rest of the article is as follows: Section 2 reviews the literature on endogenous growth model, relates R&D and patents with economic complexity. Section 3 summarizes variables, data sources and econometric models. Section 4 presents and discusses the findings. Section 5 concludes with limitations, future research suggestions, and policy implications.

2.2. Innovation Measures and Economic Complexity

2.2.1. Stylized Facts on R&D Expenditure and Patents

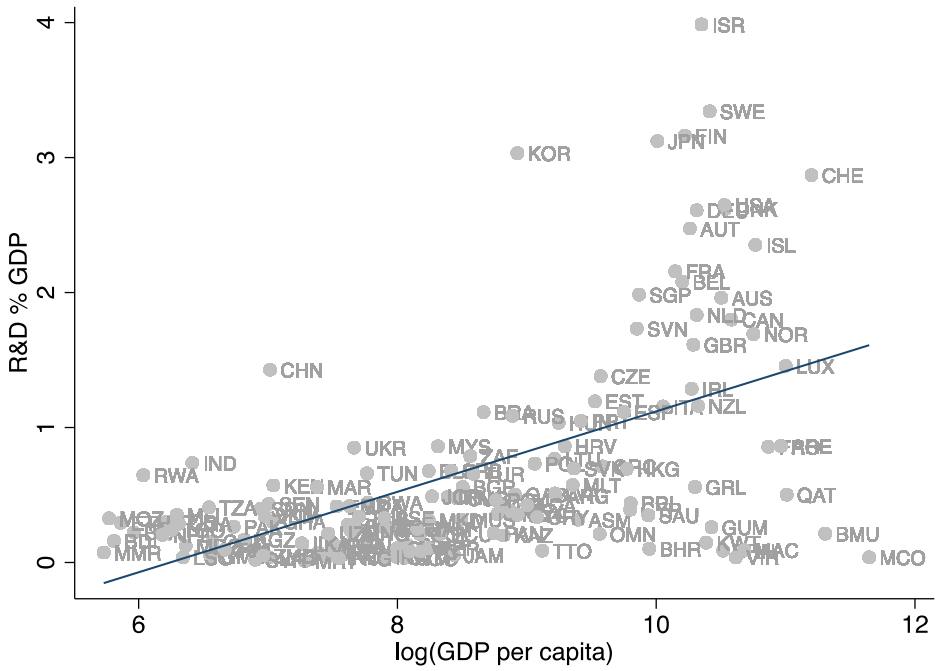
Before linking innovation measures with economic complexity, this section provides some stylized facts on R&D and patents, which helps to explain patterns of innovation measures and build empirical models. First, the histogram of R&D expenditure as a percentage of GDP shows that R&D spending across countries is not high (Figure 2.1). Around 70% of countries keep their R&D spending at less than 1% of GDP. In addition, the maximum R&D expenditure of a country does not exceed 5%. Israel and Sweden spent the highest amount on R&D, in relation to their GDP, in 2021 (Figure 2.2). As expected, countries increase their R&D spending as their income grows because they have more budget to allocate to R&D.

Figure 2.1. Histogram of R&D Expenditure.



Source: Author

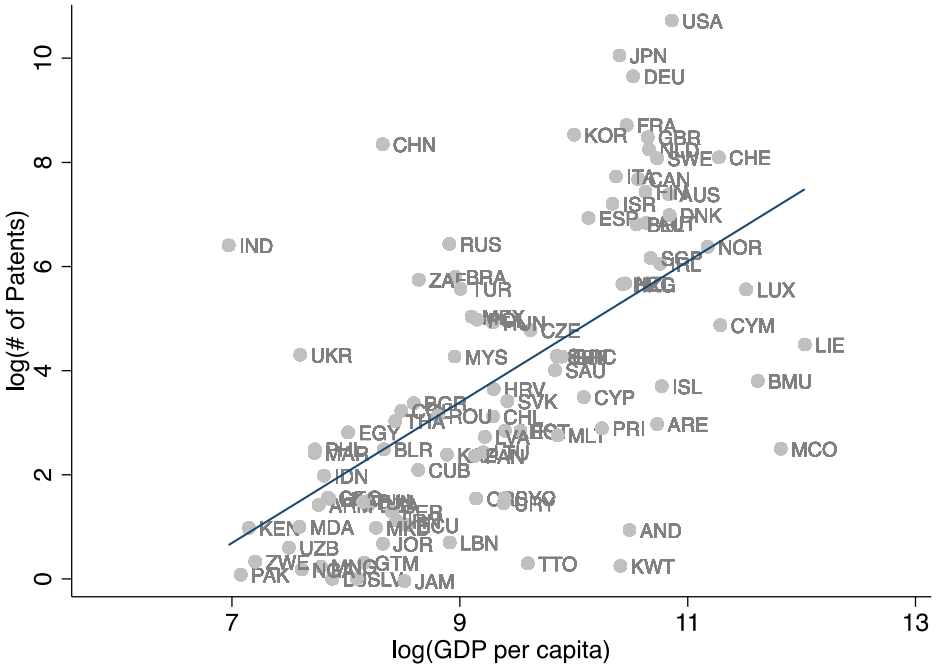
Figure 2.2. Bivariate Relation between R&D and GDP per Capita



Source: Author

Like R&D spending, the number of patents is also highly correlated with the income level (Figure 2.3). United States, Japan, and Germany hold the highest numbers of patents. Yet, Figures 2.2. and 2.3 reveal an important difference between countries' patterns on R&D spending and patenting. Countries with highest spending on R&D do not necessarily have the highest numbers of patents like Israel that supports the discussion on the advantages and disadvantages of the use of innovation measurements. There can be cultural difference towards patenting. Obviously, the United States prioritizes the patenting activity, despite its lower R&D spending than some other countries.

Figure 2.3. Bivariate Relation between Patents and GDP per Capita



Source: Author

2.2.2. Economic Complexity and Schumpeterian Approach to Trade

Schumpeterian perspective to international trade is helpful while explaining growth paradox and specialization paradox (Fagerberg, 1988, 1994). For instance, both the neoclassical theory of growth and the Heckscher-Ohlin theory of trade have shortfalls while explaining the slow growth in the United States as a frontier country and the rapid growth in Japan as a catch-up country by exporting similar commodities. Schumpeter attributes the growth to the innovation (Schumpeter, 1942) in contrast to associating growth with factor of production and exogenous knowledge. Technological progress is endogenized and reused in the production system. Catch-up countries achieve technology diffusion through imitation (Fagerberg et al., 2007). When they have the capability to exploit that technology,

they have the chance for rapid growth (Abramovitz, 1986). Howitt and Mayer-Foulkes (2005) describe R&D as a necessary technological input for such capability to achieve convergence. In an earlier work, Keller (1996) formalizes the idea of R&D as providing the initial skills to adopt diffused technology and calls it absorptive capacity. Technology diffusion alone is not enough to increase productivity; R&D is also needed (Griffith et al., 2004). At the firm-level too, R&D enhances capacity to exploit foreign technology (Cohen and Levinthal, 1989). Moreover, technology gap theory (Posner, 1961) also suggests that imitation of a frontier's innovation is needed for catching up, but continuous and significant innovative activity is more essential for surpassing the frontier (Fagerberg, 1987). R&D is both a precondition for imitation and innovation, and representative of the technological activity (Freeman and Soete, 2000).

Many scholars study the effectiveness of R&D spending, including the positive impact of R&D on total factor productivity (Herzer, 2022; Bravo-Ortega and Marin, 2011), and growth (Rouvinen, 2002; Chen et al., 2015; Gittleman and Wolff, 1995; Yi and Mah, 2016; Fagerberg, 1987), firm-level growth (Garcia-Manjon and Romero-Merino, 2012) and firm-level productivity (Aw et al., 2008). Furthermore, the interaction between science and technology, and international trade has been recognized. In support of the Schumpeterian approach to international trade, Verspagen and Wakelin (1997) explain the differences in long-term trade performance via R&D. Cross-country research finds that higher R&D is associated with a high level of technology-intensive product export (Daniels, 1993; Sandu and Ciocanel, 2014; Braunerhjelm and Thulin, 2008). Country-level studies also support the contribution of R&D in exports, for example, in the United Kingdom (Buxton et

al., 1991; Hughes, 1986), in the United States (Glick, 1982), and in East Asian countries (Alemu, 2012; Dobrzanski and Bobowski, 2020).

Like R&D spending, scholars also study the effectiveness of patenting. First, they empirically show that patents a 'fairly good' representation of innovative activity (Acs et al., 2002). Patents contribute significantly to country-level economic growth (Blind and Jungmittag, 2008; Sinha, 2008); industry-level productivity growth (Lach, 1995). As in the case of R&D, patents are also associated to countries' trade patterns. For instance, Frietsch et al. (2014) find that patents and exports are highly correlated. Patents facilitate trade in technology (de Rassenfosse et al., 2016) and have a role in the international technology diffusion (Xu and Chiang, 2005).

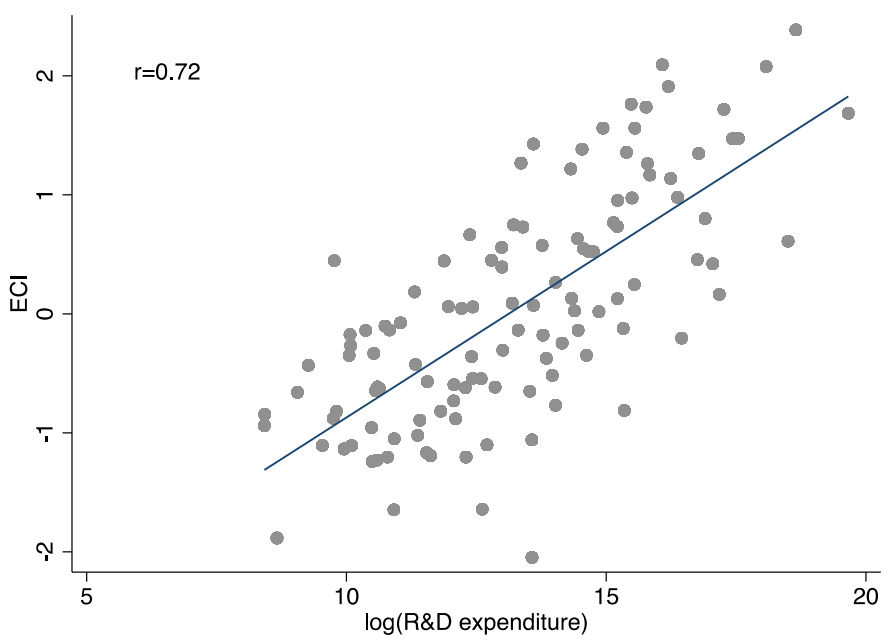
Studies about the impact of innovation measurements on diversification or sophistication are surprisingly few. There are some at the firm level (Carboni and Medda, 2018; Cirera et al., 2015; Binh and Tung, 2020) and at a regional level (Mewes and Broekel, 2020). More specifically, two studies link the innovation measurements with economic complexity. Sweet and Eterovic (2015) investigate the role of intellectual property rights and Nguyen et al. (2020) include the patents while analyzing the drivers of economic complexity. Both studies find positive impacts of these innovation measurements. I contribute to the two strands of literature. First, I include R&D spending as an innovation-related determinant of economic complexity. Second, through comparing R&D and patents, I show which innovation measurement is a better proxy in the case of analyzing economic complexity. I also consider alternative R&D and patent measures i.e., by different fields and types for a detailed analysis. Disaggregated data enables robust findings across models.

I choose ECI over other export diversity measures such as export fitness index, Herfindahl-Hirschman Index, or export concentration index, etc., because

ECI is not a simple measurement of export volume (Hidalgo and Hausmann, 2009). It takes sophistication of production into account and represents capabilities for complex production. In other words, it measures the capacity to embed knowledge as well as generate new knowledge. It is argued that technology gaps among countries occur from accumulation processes rather than differences in natural endowment (Verspagen and Wakelin, 1997). Absorbing the knowledge from technology is necessary for innovation, and R&D provides this process.

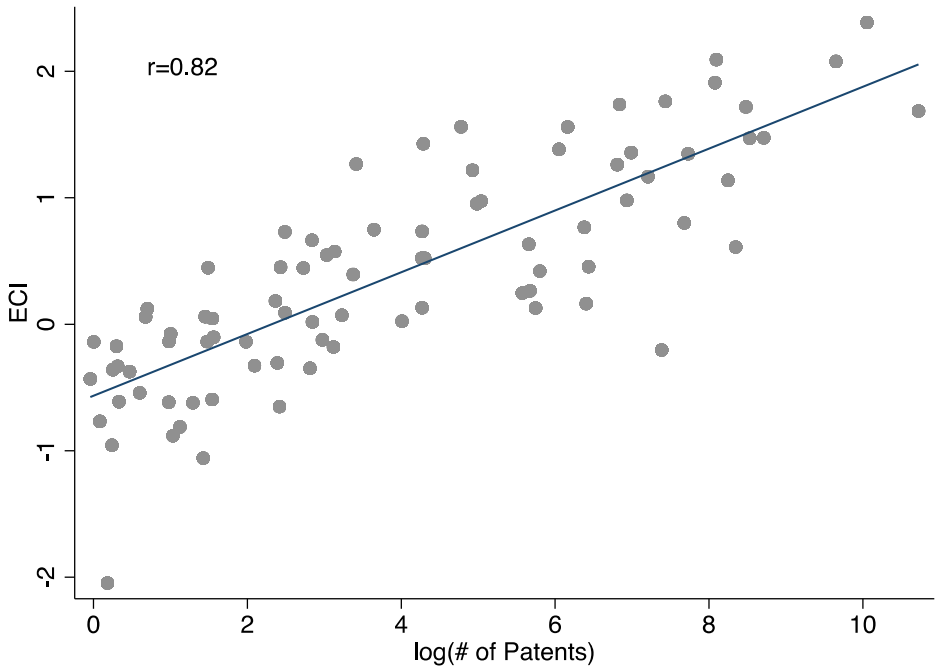
Following figures show the bivariate relationship between ECI and R&D (Figure 2.4) and ECI and patents (Figure 2.5). According to the plots, both R&D and patents are good indicators of economic complexity with a high correlation of 0.72 (for R&D) and 0.82 (for patents). And there are not outlier countries.

Figure 2.4. Bivariate relation between ECI and R&D



Source: Author

Figure 2.5. Bivariate Relation between ECI and Patents



Source: Author

2.3. Data and Methodology

2.3.1. Data

Economic complexity is the useful knowledge embedded in an economy and its resulting productive output. A country's economic complexity is measured through the diversity and ubiquity of products in its export basket. Diversity is the number of products exported, while ubiquity is the prevalence of those products. For instance, Country A exports 100 products including high-tech machinery that increases its ECI. Not all countries can build and export high-tech machinery because it requires certain knowledge and skills. On the other hand, Country B exports five products, all of which are raw materials that makes its ECI lower. In our

sample, the minimum and maximum ECI corresponds to -2.79 and 2.62 (see summary statistics in Table A2.1). ECI is available at two sources.[15]

R&D expenditure and number of patents are the main variables of interest. I use R&D as a percent of GDP from the World Bank's World Development Indicators (WDI). Alternatively, I also use R&D per capita, R&D in total amount, R&D by performance type, and R&D by field type. These disaggregated R&D data are retrieved from UNESCO's statistics. I use total number of patents data from OECD statistics. Alternatively, I use patents granted by specific patent offices such as EU and triadic families, and various patent classifications that are A: human necessities, B: performing operations, C: chemistry, D: textiles, papers, E: fixed constructions, F: mechanical engineering, G: physics, H: electricity.

I follow the literature to control for potential determinants of economic complexity.[16] First, I include GDP as R&D spending increases with economic development (Lederman and Maloney, 2003). Second, I include trade openness calculated by the trade amount as a percent of GDP. Countries that are open to international trade can also benefit from technology diffusion (Edwards, 1997). Third, I consider institutional quality using the financial institutions index. Financial development indices are commonly used as a determinants of ECI (Nguyen and Su, 2021).

Natural resource rents influence countries' R&D spending and ECI level. High resource endowment absorbs available "factors of production" into the

[15] "The Observatory of Economic Complexity" via https://oec.world/en. "The Atlas of Economic Complexity" via https://atlas.cid.harvard.edu.

[16] Correlation matrix shows that the analysis does not suffer from high collinearity among independent variables (Table A2).

resource export sector (Daniels, 1993) that could affect the relationship between R&D and ECI. I use natural resource rents as a percent of GDP. Finally, I account for human capital using secondary school enrollment. Like R&D, human capital speeds the process of technological diffusion (Nelson and Phelps, 1966). A more educated workforce facilitates the adoption and implementation of new technologies (Gittleman and Wolff, 1995). All control variables except the financial institutions index are from the WDI. The financial institutions index is from the International Monetary Fund's data.

2.3.2. Empirical Model

I employ OLS estimation including country (α_i) and time (η_t) fixed effects. Including fixed effects takes into consideration within variation (i.e., change in R&D within a country over a period) while recognizing the change in ECI. Country-fixed effects control for unobserved heterogeneity among countries, which reduces omitted variable bias. Time dummies cover shocks that may have occurred in past years as well as the change in ECI common to all countries. I take the logarithm only of GDP because other variables are either an index or a percentage. My empirical model is as follows:

$$ECI_{it} = \beta_1 Innov_{it-1} + \beta_2 trade_{it} + \beta_3 lnGDP_{it} + \beta_4 resource_{it} + \beta_5 second_{it} + \beta_6 fi_{it} + \alpha_i + \eta_t + \epsilon_{it} \quad (2.1)$$

Where $Innov_{it-1}$ represents both R&D and patent variables. To see the impact of R&D and patents in both short-term and long-term, I use lagged variables

up to five years that also reduces the simultaneity bias (Schmidt and Aschhoff, 2008; Clemens et al., 2012) on the R&D and patent coefficients.

For robustness check, I use alternative R&D and patent data. They are R&D per capita, total amount of R&D, performance type and field type. Performance type corresponds to which institutions perform R&D such as government, business, and higher education. Field types are i) medical and health sciences; ii) agriculture and veterinary sciences; iii) natural sciences, engineering, and technology; and iv) social sciences, humanities, and arts. Next, I divide the sample into sub-samples by thresholds of variables including, income level (middle- vs. high-income countries), the percentage of natural resources (lower vs. higher than 6.3%), and R&D spending (lower vs. higher than 1%).[17] I decide on thresholds with the sample mean of variables. Regarding the patent data, first, I use specific patent offices such as EU and triadic families. Second, I separate specific patent classifications which are A: human necessities, B: performing operations, C: chemistry, D: textiles, papers, E: fixed constructions, F: mechanical engineering, G: physics, H: electricity. Disaggregating data helps to understand various effects of R&D expenditures.

2.4. Results

2.4.1. R&D and Economic Complexity

Table 2.1 presents results for the baseline estimation (Equation 1), which uses the OLS estimator with country-fixed effects and time dummies. Columns 1 to 3 illustrate a sequence of models for R&D lagged by various years. R&D expenditure

[17] Keller (2002) also splits his sample into high and low R&D expenditure sectors for robustness of findings and to tackle possible endogeneity problems.

significantly improves economic complexity up to six years. The magnitude of the impact decreases over time with the most influence over a one-year gap. When controlling for other variables, the size of the effect of R&D on ECI is within a range of 0.182 and 0.132 points. Considering that ECI's sample mean is 0.005 with a standard deviation of 0.99, this effect is substantial.

Table 2.1: Short- and Long-term Impact of R&D Expenditure on ECI.

Dependent vr.: ECI	(1)	(2)	(3)
Time lags:	$R\&D_{t-1}$	$R\&D_{t-3}$	$R\&D_{t-5}$
R&D	0.182***	0.162***	0.132**
% GDP	(0.054)	(0.053)	(0.055)
GDP	0.204*	0.204*	0.197
in log.	(0.114)	(0.119)	(0.125)
Trade	0.002***	0.002***	0.003***
% GDP	(0.001)	(0.001)	(0.001)
Resources	-0.013**	-0.014**	-0.013*
% GDP	(0.005)	(0.006)	(0.006)
Secondary	0.004***	0.003**	0.003**
% gross	(0.001)	(0.001)	(0.001)
Financial i.	0.475**	0.564***	0.687***
	(0.182)	(0.211)	(0.254)
Constant	-5.496*	-5.463*	-5.400*
	(2.844)	(2.972)	(3.115)
Observations	1,181	1,083	965
R-squared	0.225	0.193	0.187
# of country	102	96	98
Country FE	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
F statistics	0	0	0

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models.

Income level, trade openness, human capital and financial institutions are significant determinants of economic complexity, which conforms to the literature

(e.g., Nguyen and Su (2021)). Natural resource rents seem to be a significant barrier to sophisticating a country's production, which is also discussed by scholars (Alsharif et al., 2017; Hausmann et al., 2013). Tables 2.1 presents remarkably consistent effect of R&D on ECI. But is the effect similar for all levels of development or all levels of R&D spending? Next, I disaggregate the data to check robustness.

Table 2.2. Total R&D , R&D per Capita and R&D by Performance Types

Depn. vr.: ECI	(1)	(2)	(3)	(4)	(5)
Type of R&D:	Total Amount	Per capita	Government	Business	Education
Unit of R&D:	*in log.*	*in log.*	*% GDP*	*% GDP*	*% GDP*
R&D	0.127***	0.123***	0.531***	0.178***	0.047
	(0.036)	(0.036)	(0.189)	(0.063)	(0.168)
GDP	0.099	0.120	0.347***	0.342***	0.335***
in log.	(0.124)	(0.122)	(0.103)	(0.117)	(0.123)
Trade	0.002***	0.002***	0.002***	0.002***	0.002***
% GDP	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Resources	-0.012**	-0.012**	-0.018***	-0.024***	-0.023***
% GDP	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Secondary	0.003**	0.003**	0.002**	0.003**	0.003**
% gross	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Financial i.	0.353*	0.312*	0.287*	0.518***	0.320**
	(0.181)	(0.181)	(0.154)	(0.187)	(0.160)
Constant	-4.282	-3.543	-8.885***	-8.798***	-8.500***
	(2.987)	(3.037)	(2.594)	(2.944)	(3.104)
Observations	1,181	1,181	1,090	972	1,052
R-squared	0.223	0.222	0.250	0.311	0.254
# of country	102	102	94	78	91
Country FE	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
F statistics	0	0	0	0	0

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models. All R&D variables are lagged by one year.

First, I replace the R&D variable with R&D total amount and per capita values. Then, I disaggregate R&D expenditure by field and performance types. Tables 2.2 and 2.3 present the results for alternative R&D variables. The total amount of R&D spending and R&D per capita are still significant and positive (Table 2.2). Their magnitudes are close to R&D per GDP. Columns 3 to 5 show three types of R&D performed by government, business enterprise, and higher education (Table 2.2). While both government- and business-performed R&D are effective on economic complexity, R&D performed by higher education is not significant. Overall, R&D in any form is still a strong factor behind economic complexity, especially government-performed R&D, which has the highest magnitude among all variables.

It is contrary to the existing literature (i.e., Guellec and Potterie (2004)) that the impact of higher education performed R&D is not significant compared to the business- and government-performed R&D. To figure out a possible explanation, I, first, plot the graph on R&D expenditure by different institutions (see Appendix Figure A2.1). While business-performed R&D has the highest amount, government- and higher education-performed R&D have the similar and lower amount of spending, yet with different effects on economic complexity. One explanation might be that government-performed R&D might target the fields such as the technological product development, which are included in the measurement of economic complexity whereas higher education performed R&D might prioritize other fields such as social sciences which are hard to include in the measurement of economic complexity. Next, as Guellec and Potterie (2004) find that the extent of the impact of R&D varies by several factors, I divide the sample into subsamples by the different education and development levels. Table A2.3 presents the results in the

Appendix. Higher education performed R&D is influential only in low- and middle-income countries that emphasizes the essential role of human capital accumulation at the beginning of the development ladder and diversification stages.

Table 2.3. R&D by Field Types

Dependent vr.: ECI	(1)	(2)	(3)	(4)
Field of R&D	Health	Agriculture	Natural sci.	Social sci.
R&D	0.014	0.062	0.100*	0.002
tot. amount in log.	(0.020)	(0.037)	(0.051)	(0.030)
GDP	-0.108	-0.231	0.070	0.008
in log.	(0.225)	(0.228)	(0.226)	(0.201)
Trade	0.002	0.001	0.003**	0.003**
% GDP	(0.001)	(0.001)	(0.001)	(0.001)
Resources	-0.034***	-0.027***	-0.027***	-0.027***
% GDP	(0.005)	(0.006)	(0.006)	(0.006)
Secondary	0.001	0.000	0.001	0.003
% gross	(0.002)	(0.002)	(0.003)	(0.002)
Financial i.	-0.182	-0.199	-0.118	-0.031
	(0.333)	(0.335)	(0.314)	(0.303)
Constant	2.768	5.417	-2.815	-0.182
	(5.569)	(5.527)	(5.499)	(4.945)
Observations	486	484	561	548
R-squared	0.292	0.304	0.288	0.252
# of country	60	59	67	66
Country FE	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
F statistics	0	0	0	0

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models. All R&D variables are lagged by one year.

Regarding the fields of R&D (Table 2.3), only science, engineering and technology fields have a significant and positive impact on economic complexity. Thus, a country's productive capabilities can be enhanced by gaining new

knowledge and skills through technology diffusion (Keller, 2004). Also, considering the fact that economic complexity is calculated by the diversification and sophistication of a country's export basket, R&D spent on health, agriculture, or social sciences are reasonably not expected to increase the economic complexity level. I also draw the plot on R&D expenditures by fields (see Appendix Figure A2.2). The significant impact of R&D spent on science, engineering, and technology fields is reasonable because other three fields of R&D have quite lower amount of spending. A shortfall of results in Table 2.3 is the lack of data for some years and some countries for different fields of R&D. Fewer observations also affect the coefficients for control variables except natural resource rents, which show consistent impact across all models.

Next, I divide the sample into sub-samples for the possibility of an insignificant effect of R&D under various conditions (Table 6). I determine the thresholds by three metrics: R&D spending, income level, and natural resource rents. For the income level I use the World Bank's classification of countries as high income, middle income, and low income. For R&D and natural resources I use the sample mean as a base, and both values result in a threshold for R&D to be impactful. The limitation of sub-samples is dropped observations and issues of comparison across models of unequal sample size. Nevertheless, results are insightful and intuitive.

First, it is visible that for R&D spending to be effective, it should be higher than 1% of GDP. Because only approximately 30% of countries spend more than 1%, countries should allocate more budget to R&D to benefit from it. Having a threshold for R&D to be influential is consistent with the literature. Hughes (1986) claims that R&D above a certain level can lead to export of R&D-intensive products

while R&D below the required input cannot bring in production. Second, I compare high-income and middle-income countries. R&D is effective in both levels of development, but middle-income countries enjoy the benefits of R&D more than high income countries. This finding contrasts with R&D's significance in explaining GDP variation among more developed countries as found by Gittleman and Wolff (1995).

Table 2.4. Dividing into Subsamples by Thresholds.

Dep. vr.: ECI	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	R&D<1	R&D>1	Low & Mid. Inc.	High Income	Resource< 6.3	Resource> 6.3
R&D	0.145	0.177***	0.359***	0.144**	0.141**	0.258
% GDP	(0.115)	(0.051)	(0.083)	(0.057)	(0.060)	(0.156)
GDP	-0.129	0.715***	-0.291**	0.612***	0.338***	-0.828***
in log.	(0.145)	(0.167)	(0.141)	(0.155)	(0.108)	(0.194)
Trade	0.002***	0.001	0.001	0.002**	0.002***	-0.001
% GDP	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Secondary	0.006***	0.000	0.005***	0.001	0.004***	0.005*
% gross	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Resources	-0.014***	-0.030***	-0.015***	-0.011**	-0.017	-0.006
% GDP	(0.005)	(0.008)	(0.006)	(0.004)	(0.012)	(0.005)
Financial i.	-0.064	0.378	-0.070	0.446**	0.307	-0.412
	(0.238)	(0.234)	(0.208)	(0.209)	(0.191)	(0.512)
Constant	2.653	-18.21***	6.748*	-15.63***	-8.704***	20.143***
	(3.585)	(4.447)	(3.469)	(4.068)	(2.738)	(4.833)
Observation	763	479	686	556	1,035	207
R-squared	0.217	0.524	0.284	0.399	0.227	0.484
# of countries	82	38	72	42	88	35
F statistics	0	0	0	0	0	0
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time dum.	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models. All R&D variables are lagged by one year.

Third, I compare resource-endowed and -abundant countries. As seen in Table 2.4, R&D is effective when there is a low percentage of natural resources (less than 6.3%). This is reasonable because countries with higher resource rents do not spend much on R&D. Therefore, a low amount of R&D expenditure cannot result in improving productive capabilities.

2.4.2. Patents and Economic Complexity

In this section, I present results for various patent data as the innovation measurement instead of R&D spending. First, I include patents filed under different offices; i) all international patents represented by PCT, ii) patents filed under triadic families, and iii) patents filed in the European patent office. Table 2.5 shows that all patents filed under different offices have positive and significant effect on economic complexity. The magnitude of the impact ranges between 0.02 and 0.04. International patents have the largest effect that is followed by European office and triadic families. Even though the correlation between patents and ECI were higher than the correlation between R&D and ECI, the magnitude of the impact in the regression analysis is higher for R&D than patents. It can be because the effects of control variables in the regression are higher for patents that is visible through the R-squared in both analyses. Larger R-squared in the regressions with R&D show that R&D slightly better corresponds to the change in ECI (R-sq.=0.223) compared to the proportion of patents in explaining the change in ECI (R-sq.=0.166).

Table 2.5. All Patents, Triadic Patents, and European Patents

Dependent vr.: ECI	(1)	(2)	(3)
Patent office	PCT	Triadic	EPO
# of Patents	0.044***	0.021**	0.038**
in log.	(0.016)	(0.009)	(0.018)
GDP	0.142	0.184	0.160
in log.	(0.115)	(0.116)	(0.119)
Trade	0.002***	0.002**	0.002*
% GDP	(0.001)	(0.001)	(0.001)
Resources	-0.012**	-0.013***	-0.012**
% GDP	(0.005)	(0.005)	(0.005)
Secondary	0.002*	0.002**	0.002**
% gross	(0.001)	(0.001)	(0.001)
Financial i.	0.306	0.320*	0.276
	(0.187)	(0.180)	(0.190)
Constant	-3.705	-4.733	-4.140
	(2.913)	(2.927)	(2.997)
Observations	1,303	1,284	1,303
R-squared	0.166	0.159	0.158
# of countries	79	79	79
F statistics	0	0	0
Country FE	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models. All patent variables are lagged by one year.

Table 2.6 presents results for alternative patent classifications. Positive and significant effects of patents on economic complexity are valid for types A: agriculture and health, B: performing operations, C: chemistry, and G: physics. As seen in the summary statistics for IPC classifications (Appendix Table A2.4), these are the classes with the high amounts of patents filed. In overall, control variables have consistent results with the previous table.

Table 2.6. Alternative Patent Classifications.

Dep.vr.:ECI	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patent class	IPC A	IPC B	IPC C	IPC D	IPC E	IPC F	IPC G	IPC H
# of Patent	0.038***	0.034***	0.031***	0.015	0.013	0.014	0.032**	0.02
in log.	(0.014)	(0.011)	(0.012)	(0.016)	(0.017)	(0.014)	(0.014)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,916	1,916	1,916	1,916	1,916	1,916	1,916	1,916
R-squared	0.155	0.154	0.152	0.140	0.140	0.140	0.154	0.144
# of country	79	79	79	79	79	79	79	79
F statistics	0	0	0	0	0	0	0	0
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models. All patent variables are lagged by one year.

2.4.3. Comparing R&D with Patents

In this section, I intend to compare the impacts of R&D spending and patents on economic complexity. Table 2.7 presents the results. Column 1 includes only total amount spent on R&D, Column 2 includes the number of all international patents, and Column 3 includes both innovation measurements together in the regression. Both R&D and patents have positive and significant impact on economic complexity individually and together. Magnitude of the impact is smaller for patents compared to R&D. More importantly, when two variables included in the regression, their effects are still significant. They only slightly lessen each other's impact. According to Column 3, economic sizes of the impacts of both measurements as follows. One standard deviation growth in R&D spending (i.e., from the mean of USD 13 million to 46 million) brings in 10% rise in ECI (from the mean of 0.58 to 0.64). Similarly, one standard deviation growth in patents (i.e., from the mean of 1528 to 6147 filed patents) brings in 4% rise in ECI (from the mean of 0.58 to 0.60). Both impacts are economically significant and high.

Table 2.7. R&D, Patents, and Economic Complexity

Dep. vr.: ECI	(1)	(2)	(3)
Innovation measure	R&D	Patents	R&D and Patents
R&D	0.122***		0.097**
Tot. amount in log.	(0.036)		(0.042)
# of Patents		0.044***	0.040*
PCT in log.		(0.016)	(0.021)
GDP	0.085	0.142	0.053
in log.	(0.127)	(0.115)	(0.129)
Trade	0.002***	0.002***	0.0025***
% GDP	(0.0007)	(0.0007)	(0.0007)
Resources	-0.012**	-0.012**	-0.009*
% GDP	(0.00507)	(0.0049)	(0.0054)
Secondary	0.0026**	0.0018*	0.0021*
% gross	(0.001)	(0.001)	(0.00107)
Financial i.	0.364*	0.306	0.412**
	(0.189)	(0.187)	(0.021)
Constant	-3.846	-3.705	-2.790
	(3.089)	(2.913)	(3.098)
Observations	1148	1,303	1,077
R-squared	0.215	0.166	0.214
Number of country	101	79	79
Country FE	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
F statistics	0	0	0

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS estimator with country fixed effects and time dummies is used in all models. Both innovation variables R&D and patents are lagged by one year.

2.5. Concluding Remarks

In this study, I examine the relationship between R&D spending, patents, and economic complexity as representative of productive and innovative capabilities. I find a remarkably robust and positive impact of R&D and patents on economic complexity for a world sample. The impact of R&D is stronger and more robust than

the impact of patents. However, alternative estimations by sub-samples indicate some limitations. For instance, R&D spending becomes influential when it is higher than 1% of GDP. Having a minimum threshold for R&D effectiveness supports Hughes' (1986) study. In addition, only countries with low natural resource rents can benefit from R&D because countries with high resource endowment do not spend much on R&D. Fortunately, developing countries benefit from R&D in terms of rising productive capabilities much more than developed economies. Once a country reaches a certain level of development, change in productive capabilities are smaller than countries who are at the beginning of a development ladder. This process is aligned with the convergence hypothesis on growth.

Moreover, I find both business- and government-performed R&D impactful while there is no effect from higher-education-performed R&D. Finally, natural science, engineering and technology are the only fields that R&D's impact seems visible. Other fields such as social science, medicine, and agriculture have no effect on the sophistication of production and exports. In similar vein, the effect of patents is robust for various patent offices whereas the results get mixed when I take into account specific patent classifications.

These findings do not imply that innovation measurements -either R&D or patents - solely determine the productivity growth or economic development. As discussed in the Section 2, R&D is a necessary input to improve the productive capabilities for innovation. And patents represent the tangible outcome of innovative activity. This study adds to the literature, which shows the absorptive capacity of R&D not only in growth (Keller, 1996, 2004; Cohen and Levinthal, 1989) but also in sophisticating exports. R&D enables countries to progress to new industries by reducing cost and risk (Mewes and Broekel, 2020). By jumping from one related

industry to another, countries increase their level of economic complexity (Hidalgo and Hausmann, 2009; Hausmann et al., 2013). Additionally, R&D can facilitate this process also by learning and absorbing new knowledge and skills, necessary for the new industry. Furthermore, It supports and broadens Nguyen et al. (2020) study which finds a positive effect of patents on economic complexity.

A limitation of this study is the lack of cross-country data on R&D especially for early years such as the 1970s to the 1980s. Within this period, catch-up countries had achieved the technical change. For instance, Brazil had raised its economic complexity level from -0.9 in 1965 to 0.4 in 1990. Observing latecomers benefitting from R&D while growing their innovative activities would provide stronger evidence. Likely, R&D data is missing for low-income countries, so it is unknown whether spending on R&D would benefit their diversification.

Finally, there is an ongoing debate on the use of R&D and patents as innovative measurements. Advantages and disadvantages exist for each measurement. For instance, not all R&D spending aims for innovation. Or R&D does not include all product innovation expenditure. On the other hand, patents are actual outcomes. Yet, patenting does not occur for each invention. Likely, patenting culture is not common in every country. The choice of R&D or patents as an innovation measurement can be decided by the research question, empirical model, and context of the study. In the case of economic complexity, R&D seems to be a better proxy than patents. It can be stem from the fact that economic complexity represents knowledge and skills embedded in an economy. In that sense, R&D is more comprehensive proxy because patents capture only the explicit side of the innovation rather than the tacit knowledge accumulation.

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Appendix

Table A2.1. Summary Statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
ECI	5828	.005	.994	-2.791	2.625
R&D *(% GDP)*	1981	.925	.935	.005	4.941
GDP (log)	9598	23.632	2.339	16.811	30.625
Trade *(% GDP)*	8376	78.178	54.099	.021	863.195
Resource *(% GDP)*	8775	6.587	10.856	0	87.507
Secondary *(% gross)*	6530	66.132	34.289	0	166.146
Financial Ins.	7320	.331	.222	0	1
# of Patents *(IPC A)*	2099	251.12	936.57	0	9372.45
# of Patents *(IPC B)*	2095	312.41	1246.26	0	13281.07
# of Patents *(IPC C)*	2100	195.2	781.68	0	6483.61
# of Patents *(IPC D)*	2098	21.73	78.223	0	617.56
# of Patents *(IPC E)*	2098	51.42	172.985	0	2033.66
# of Patents *(IPC F)*	2098	179.792	706.57	0	6048.14
# of Patents *(IPC G)*	2099	459.306	1962.66	0	18618.65
# of Patents *(IPC H)*	2100	508	2138.04	0	20496.02

Table A2.2. Correlation Matrix.

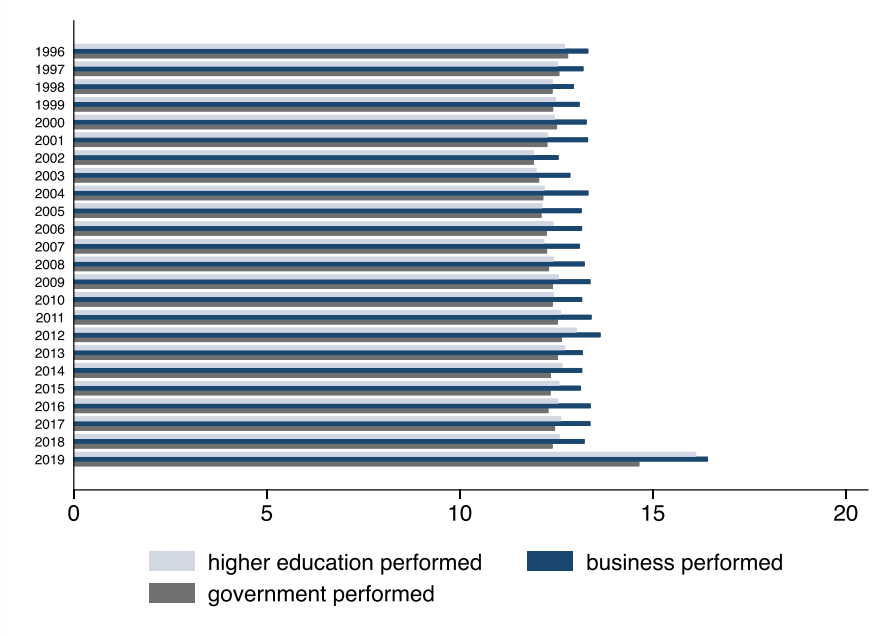
	R&D	GDP	Trade	Resource	Second.	Financial i.	Patent
R&D *(% GDP)*	1.000						
GDP *(log)*	0.499	1.000					
Trade *(% GDP)*	0.021	-0.257	1.000				
Resource *(% GDP)*	-0.287	-0.059	-0.133	1.000			
Second. *(% gross)*	0.519	0.340	0.178	-0.184	1.000		
Financial i.	0.653	0.515	0.255	-0.302	0.624	1.000	
Patent *(log)*	0.754	0.765	0.003	-0.328	0.471	0.710	1.000

Table A2.3. Higher Education Performed R&D Spending by Subsamples

Dep. vr.: ECI	(1)	(2)	(3)	(4)
Sample:	Tertiary < 26.8	Tertiary > 26.8	Low & middle i.	High income
R&D	0.635	-0.034	0.350*	0.018
% GDP	(0.505)	(0.181)	(0.175)	(0.185)
Controls	Yes	Yes	Yes	Yes
Observations	161	870	554	498
R-squared	0.405	0.226	0.288	0.464
# of country	39	74	62	40
Country FE	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
F statistics	0	5.49E-06	0	0

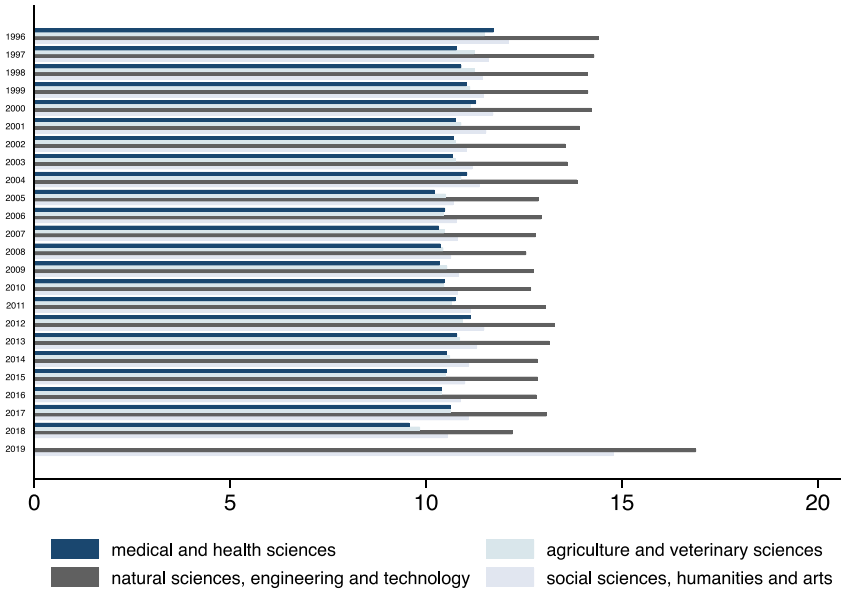
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. OLS fixed effect with time dummies is used in all models. All R&D variables are lagged by one year.

Figure A2.1. R&D Expenditure by Performance Types



Source: Author

Figure A2.2. R&D Expenditure by Field Types



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Chapter III

Environmental Policies, Institutional Quality, and Green Innovation

3.1. Introduction

Growing crisis on the climate change shows an immediate need for innovation in green technologies. Dealing with global challenges on environment is possible with developing alternative energy sources. There is an urgent need of technologies which uses fewer resources with fewer greenhouse gas emission. Countries rise their pledges on clean environment-related goals, but efforts are not sufficient because, meanwhile, market failure brings in negative externalities on the environment. In that regard, government intervention through green industrial policies is recalled by scholars (i.e. Rodrik (2014)). For instance, Acemoglu et al. (2012) proposed the directed technical change to reorient the innovation from dirty to clean inputs because there is an excess R&D spending on dirty innovation. Such intervention moderates the production cost in clean innovation. Putting state intervention into the center stage reminds the significant role of institutional frameworks.

Existing literature uses two policy instruments while investigating the determinants of green innovation. First, it focuses on the energy pricing. Induced innovation hypothesis claims that increased energy prices redirect innovators towards energy-efficient technologies (Popp, 2002). Other studies also support the induced innovation both at firm/industry-level (Aghion et al., 2016; Newell et al., 1999) and country-level (Johnstone et al., 2010). Second, it empirically analyzes the catalyzer role of environmental policies on green innovation. However, institutional environment as a necessary condition for successful policy implementation is surprisingly limited. Nesta et al. (2014) take into consideration competition/market liberalization and show its mediator role in green innovation. Fabrizi et al. (2018) find that the positive impact of environmental policies is conditional on the network participation among European Union countries.

This study fills the gap by revealing the complementary roles between policies and institutional environment on green innovation. It claims that both environmental policies and institutional quality cause to innovation in environment-friendly technologies. It also expects policies are more effective with better institutions. I use International Country Risk Guide's (ICRG) political variables as proxy for institutional quality. Depending on the availability of the data, I cover 31 countries between 1990 to 2019. Because of the count structure of patent data as dependent variable, my model has Poisson distribution. To tackle heterogeneity in panel setting, I employ presample mean scaling estimator to control for fixed effects (Blundell et al., 1999). To deal with possible endogeneity bias, I also implement instrumental variable strategy with a control function approach.

I find a significant and positive impact of environmental policies and institutions on green innovation. Their joint effect does not necessarily result in more

innovation. Findings are robust to controlling for R&D spending, which is the main input for an innovative outcome. Alternative variables and models also provide strong and robust results. Finally, using democratic durability as an instrument on policies, I show that the effect of policies on innovation is causal and not due to the self-selection.

The rest of the paper is organized as follows. Section 2 presents the literature on induced innovation, green policies, and institutions. It then makes a connection between them and builds hypotheses. Section 3 explains the data, and econometric models. Section 4 discusses the findings and Section 5 concludes.

3.2. Driving Factors for Green Innovation

Environmental Policies

How innovators respond to environmental policies has received a growing attention. Market failure produces negative externalities on the environment due to insufficient clean innovation and too much R&D expenditure on dirty technologies. Theoretical models of climate change with endogenous technical change present some solutions (Buonanno et al., 2003). For instance, Acemoglu et al. (2012) argue that carbon taxes and research subsidies on clean inputs can redirect the innovation from dirty to clean technologies.

Two measurements are applied for policies at the country level research that are environmental policy stringency (EPS) and R&D expenditure. Broad literature finds positive impacts of environmental policies and environment-related R&D spending on environmental patents (Johnstone et al., 2010; Nesta et al., 2014; Johnstone et al., 2012; Fabrizi et al., 2018; Sterlacchini, 2020). Positive impact of EPS is also found in green productivity (Wang et al., 2019).

Hypothesis 1. More stringent environmental policies, higher the green innovation.

Institutional Quality

Acemoglu et al (2012) emphasize a temporary government intervention to redirect the innovation from dirty to clean technologies under laissez-faire. Similarly, Rodrik (2014) points out the need for an institutional design while accomplishing the green industrial policies. He carries three ideas on which green industrial policies should be built that are embeddedness, discipline, and accountability between public and private sectors. Putting the government intervention again at the center stage in the short or long term reminds us of the importance of institutional environment[18].

Studies on the role of institutions on green technology innovation have an increasing trend. Zhao et al. (2021) find that increased financial risk[19] directly reduces CO2 emissions and increases technological innovation. In addition, Chaudhry et al. (2021) show that institutions[20] have negative impact on environmental indicators. Moreover, Sun et al. (2019) examine the support of reliable government institutions[21] for adopting green technology. Lastly, while

[18] Rodrik (2014) provides the example of South Korea's developmental state model while explaining those three key ideas behind the industrial policy design. More literature on the role of institutions in East Asian developmental states can be found via (Crafts, 1999; Ahmad and Hall, 2012; Rock, 2013; Keefer, 2011; Ito and Chinn, 2007). These studies mostly use ICRG indicators in the empirical analysis including bureaucratic quality, corruption, law, and accountability measurements.

[19] They use Financial Risk Rating from ICRG.

[20] They compose an institution index from five indicators of ICRG.

[21] They combine five categories from the World Economic Freedom Index for the institutional quality.

measuring the impact of terror indices in innovation of renewables technologies, Zheng et al. (2021) control for domestic institutional variables[22].

Based on the existing literature which includes various institutional variables, I prefer to use bureaucratic quality as a proxy for institutions. Environmental policies require long-term implementation of policies. Institutional framework in terms of continuation of policy implementation is important. Change in governance should not cancel the policies. Bureaucratic quality index from ICRG is defined as how institutions absorb the shock and minimize the revision of policies due to the change in governments.

Hypothesis 2. Better bureaucratic quality, higher the green innovation.

Conditional impact of policies on institutions

Environmental policies are expected to be more efficient when conducted in well-designed institutional environment. It is because implementation of those policies requires long-term and stable political medium, as well as economic and social support. Two studies investigate the joint effects of policies and institutional environments. First, Nesta et al. (2014) estimate the impact of policies on innovation under competitive markets. They find that renewable energy policies are more effective in countries with liberalized energy markets. Second, Fabrizi et al. (2018) estimate the conditional impact of policies with network participation. They show that market-based regulation policies and participation in green research networks have complementary role in environmental innovation. In a similar vein, this study

[22] They use stability and corruption from ICRG.

aims to investigate the joint effects of green policies and institutions on green innovation.

Hypothesis 3. Policies implemented with higher bureaucratic quality, higher the green innovation.

Induced Innovation

Another motivation behind the innovator's reorientation towards green technologies is the change in prices. Hicks (1932) introduced the induced innovation hypothesis that rise in factor prices leads to the innovation which does not use those expensive inputs. An early work which tests Hicks' hypothesis is conducted by Newell et al. (1999) on air-conditioning industry. Next, Popp (2002) estimates the effect of energy prices on the energy-efficient innovation. Aghion et al. (2016) find similar results for the auto industry that increased fuel prices cause firms to innovate in clean technologies. Cross-country studies use electricity price (Nesta et al., 2014; Johnstone et al., 2010) and oil prices (Sterlacchini, 2020) on green patents and find mix results. In this study, I discuss the shortfalls of both electricity prices and crude oil import prices. Rather, I prefer to use environment-related taxes provided by IMF data as they better proxy for carbon pricing at the country level. I expect to find their positive impact on the environment-friendly patents.

Hypothesis 4. Higher the energy prices, higher the green innovation.

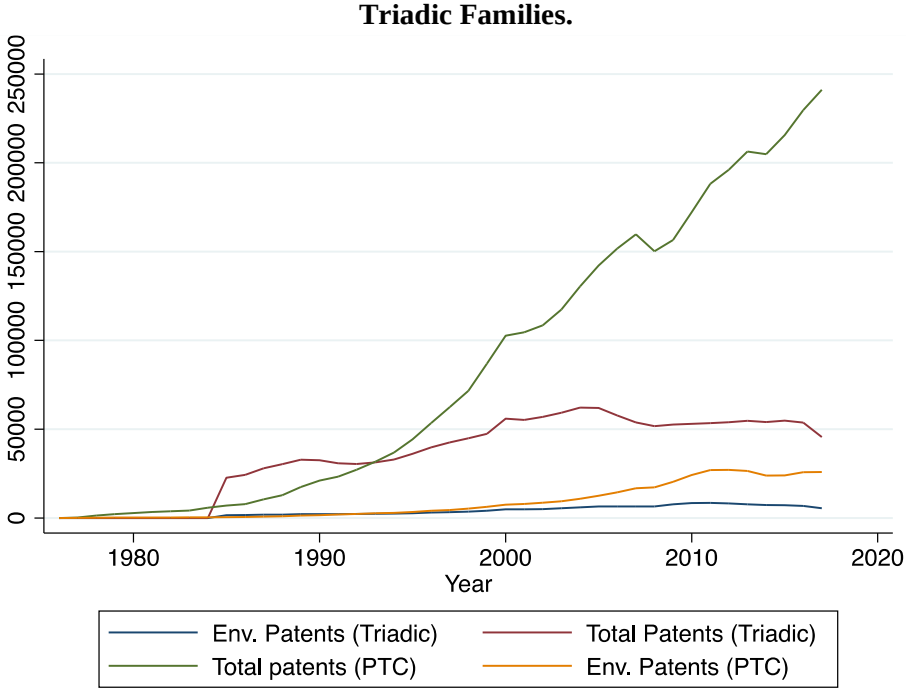
3.3. Data and Methodology

3.3.1. Data

I use the OECD's patent data for environment-friendly technologies as the dependent variable. I use patens filed under the Patent Cooperation Treaty (PTC) for baseline

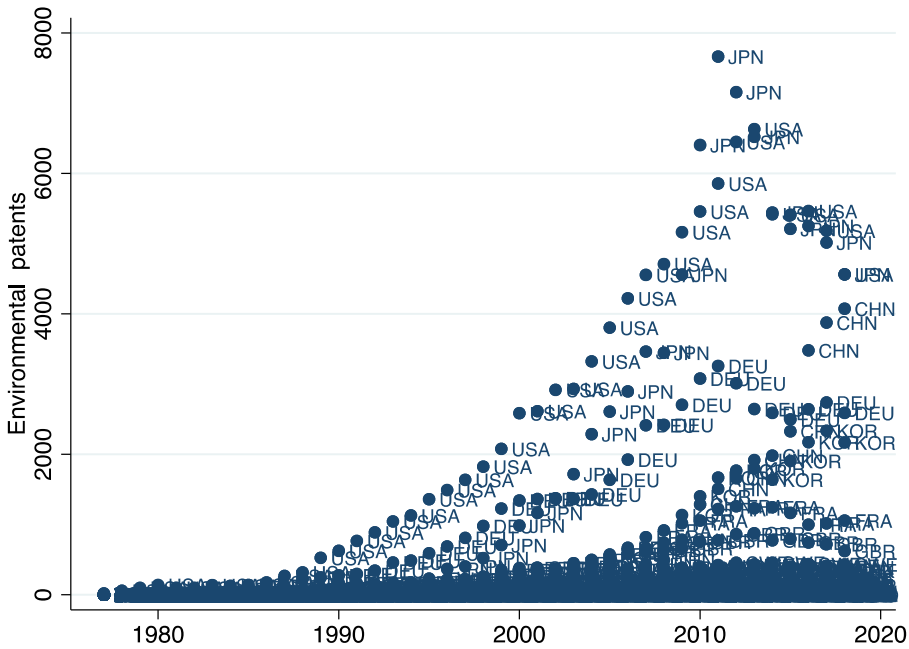
estimations and triadic patent families for the robustness checks. OECD derives the data from Worldwide Patent Statistical database, PATSTAT. Patent data is available from 1976 to 2019. Depending on the availability of all variables, the panel dataset covers the period of 1990-2019 for 31 countries. Table for country list can be found in Appendix. Figure 3.1 presents the trends on patents for the World. Patents including all technology domains have an increasing trend since 1980s whereas environment-related technologies rise after 1990s. Triadic families are obviously fewer than patents filed under PTC. Figure 3.2 focuses on only environment-friendly patens filed under PTC. United States, Germany, Japan, South Korea, and China are leading countries in green innovation.

Figure 3.1. World's Trends on Environmental and Total Patents by PCT and Triadic Families.



Source: Author

Figure 3.2. Change in Environmental Patents by Country.



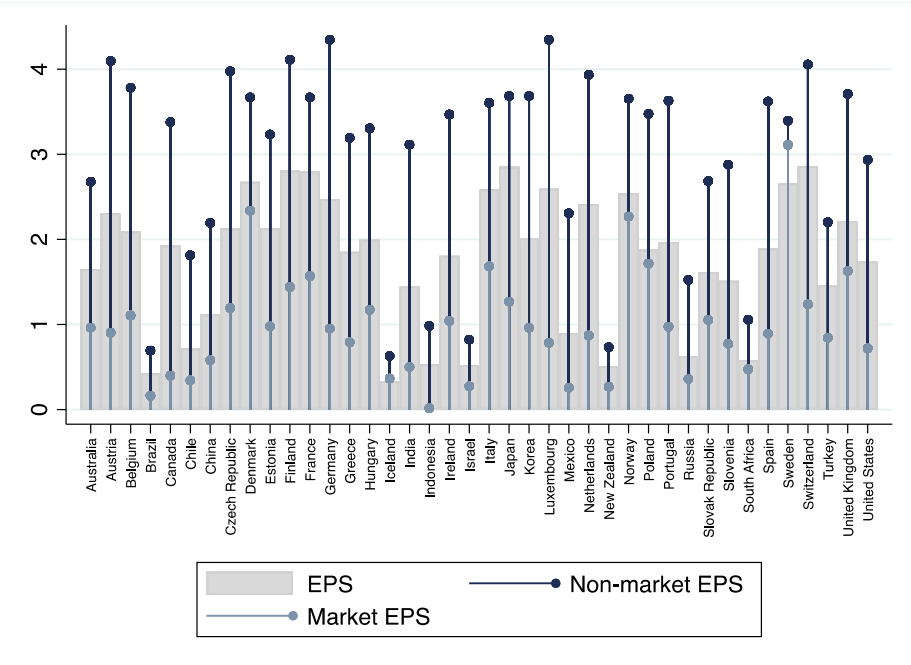
Source: Author

Country-level studies mostly use electricity prices and crude oil import prices which are available from OECD. Findings on electricity and oil prices' impact on green innovation are mixed in the literature (Johnstone et al., 2010; Nesta et al., 2014; Sterlacchini, 2020). One reason is that electricity can be generated by clean technologies like the renewables yet at high cost. Therefore, increased electricity prices do not necessarily cause to the use of renewables in electricity generation. Second, crude oil import prices do not vary across countries (Figure A3.1) rather, international oil prices respond to global shocks and vary over years (Figure A3.2), so the inclusion of time dummies as well as country fixed effects can absorb its effect. In Appendix (Table A3.4), I present results for crude oil and electricity prices. In line with the literature, they have no significant effect. In this study, I use environment-related taxes from IMF as a better proxy for the carbon pricing at the

country-level. Data includes taxes for environment, energy, pollution, transportation, and resources.

As a main variable of interest, environmental policy stringency (EPS) is also available at OECD statistics (Kruse et al., 2022). Stringency means the degree to which environmental policies put an explicit or implicit cost on polluting or environmentally harmful behavior. EPS index is available for each policy type that are (i) taxes, trading schemes, feed-in-tariffs (grouped as market EPS) and (ii) standards, R&D subsidies (grouped as non-market EPS). Figure 3.3 shows the average EPS value for each country within the period. It also presents the difference between market and nonmarket EPS. Japan and Switzerland are among the most stringent countries whereas Brazil and Iceland are the least stringent. I also include dummy variable for Kyoto ratification of countries. Because after signing the Kyoto treaty countries have put an emphasize on environmental policies.

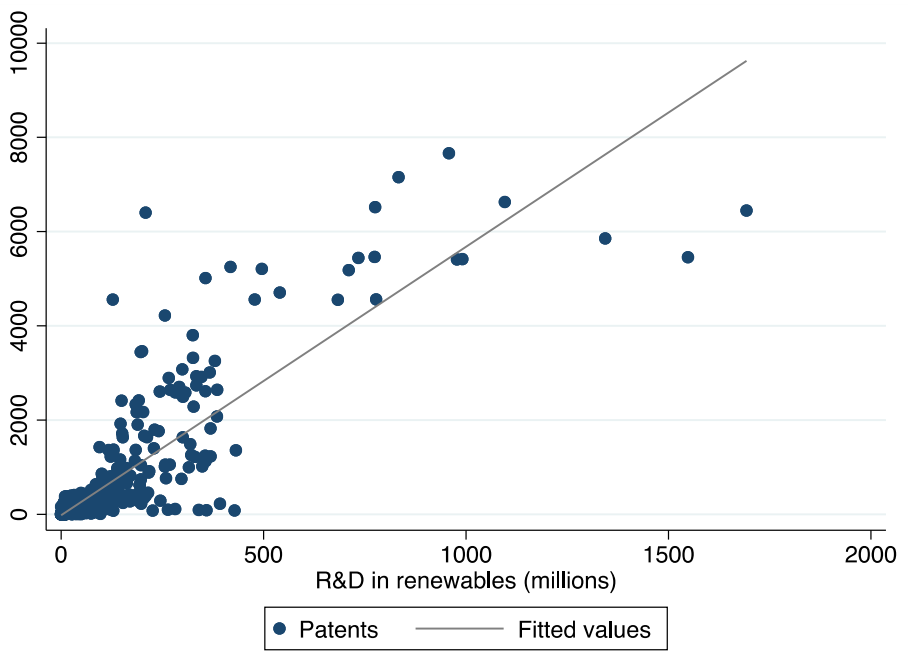
Figure 3.3. Averaged EPS, Market EPS, and Nonmarket EPS for Countries.



Source: Author

Although EPS index contains R&D subsidy stringency, the actual amount of R&D spending is an essential input for the innovative outcome. As the endogenous model of climate change (Acemoglu et al 2012) shows, R&D is a determinant of the clean innovation. I use R&D spending on renewable energies (also overall energy types for robustness) from International Energy Agency database. Figure 3.4 shows the bivariate relationship between R&D spending on renewables vs. environmental patents. They are highly correlated (r=0.8).

Figure 3.4. Bivariate Relation between R&D Spending in Renewables and Environmental Patents.



Source: Author

Knack and Keefer (1995) introduce the ICRG political indicators while estimating the effect of institutions on economic development. They argue that ICRG indicators are better measurement of institutions based on property rights.

ICRG indicators are also broadly used in environment-related studies[23]. I use bureaucratic quality among ICRG indicators because it measures the institutional strength to absorb the shock and minimize the revision of policy when governments change. Its range covers from zero to four. Countries with higher bureaucratic quality receive higher points. For robustness test, I use political risk rating from ICRG that composes all political indicators and assesses the political stability.

For the control variables, I simply include GDP per capita and Greenhouse Gas (GHG) emission from World Bank's World Development Indicators. Summary statistics and correlation matrix are provided in the Appendix (Tables A3.2 & A3.3).

3.3.2. Empirical Model

Following the Poisson distribution, the main model is as follows:

$$E(EnvPat_{it}|x_{it}, \omega_{it}, \eta_i, \tau_t) = \exp(\alpha x_{it} + \beta\omega_{it} + \eta_i + \tau_t) \qquad (3.1)$$

Where x_{it} are the main regressors of interest including price, policy, and institutions. Next, ω_{it} are the control variables, R&D spending, GDP per capita and GHG emission in kt. Lastly, η_i is a country fixed effect, and τ_t are time dummies. I use the log-link formulation due to the count-based nature of patens. Although I apply alternative estimators considering different assumptions on the error term, equation (3.1) remains the same[24]. The baseline is the Poisson model, where the mean equals the variance. I also consider Negative Binomial, which relaxes this assumption.

[23] Section 2 indicates some literature which uses ICRG indices in studies of institutions and environment.

[24] Hypotheses 1, 2, and 4 are tested through the Equation 1. For Hypothesis 3, I include the interaction term between policy and institution variables into Equation (1).

Cross-country heterogeneity is an essential feature of panel dataset to deal with. Country fixed effects control for country-specific time-invariant unobserved variables. The prominent literature includes two versions of fixed effects. First, Hausman et al. (1984) introduced the fixed effect Poisson model. However, it requires the strict exogeneity assumption. Second, Blundell et al. (1999) introduced "presample mean scaling" (PSM) model which relaxes the strict exogeneity assumption. Especially, it is useful when there is a long presample history on the dependent variable to construct the presample average. In my case, environment-friendly patents have a presample data (up to 15 years) that can be used as an initial condition to proxy for unobserved heterogeneity. It also provides the condition that the first moments of the variables must be stationary. Blundell et al. (2002) show that using PSM as fixed-effects more consistent than quasi-differenced GMM and/or traditional fixed effects for dynamic panel data models with weakly endogenous variables.

PSM is calculated as follows:

$$\overline{EnvPat_i} = (\frac{1}{TP}) \sum_{r=0}^{TP-1} EnvPat_{i,0-r} \tag{3.2}$$

Fixed effects η_i in Equation (1) becomes

$$\eta_i = \gamma ln\overline{EnvPat_i} \tag{3.3}$$

Robustness Checks

In addition to comparison of alternative estimators, I provide robustness check using alternative measurements of variables. First, I add more control variables which are used in the literature such as the Kyoto ratification. Second, I replace the patent data signed under PTC with triadic patents. Third, I replace R&D on renewables with R&D on all energy sectors. Fourth, I include environment-related taxes. Fifth, I replace bureaucratic quality with overall political risk rating from ICRG. Sixth, I replace variables with per capita values and include population as a control variable.

3.3.3. Identification Strategy

The coefficient on EPS may be biased because of the reverse causality from innovation to policies. For example, successful innovations in environment-friendly technologies push innovators to lobby for environmental policymaking. Another problem can be measurement errors for the policy variable. Different environmental policies can affect patents in different way. By using an aggregated index for overall policy stringency rather than continuous variables for the actual amount of each type of environmental policies, I likely to underestimate the impact of policies on patents. I deal with endogeneity issues by using democratic durability as an instrumental variable for environmental policy stringency.

There is a growing literature about the positive impact of democracies on stringent environmental policies (Congleton, 1992; Fredriksson et al., 2005; Neumayer, 2002; Chang and Berdiev, 2011). In this regard, longer democratic durability is expected to ensure environment-friendly policymaking and long-term implementation compared to younger democracies. For instance, Neumayer (2002) claims that democracies ratify more multilateral agreements, have a national council

and relevant information on the environment. Likely, Fredriksson et al. (2005) argue that political competition tends to increase policy stringency as a result of citizens' participation in democracy. I use TENSYS index provided by the World Bank Database on Political Institutions (Beck et al., 2001) to proxy for the time length in which democratic institutions have been consolidated and durable.

I employ control function approach (Blundell and Powell, 2004; Wooldridge, 2015) instead of two-stage least squares (2SLS) because I have nonlinear count data models. When there is a continuous endogenous variable in a nonlinear count data model 2SLS is no longer consistent. Control function also consists of two stages but differently from 2SLS, it includes residuals from the first stage of OLS estimation as a control variable in the second stage of nonlinear count data model.

$$EPS_{it} = \pi TENSYS_{it} + \beta^{o}\omega_{it} + \eta_i^{o} + \tau_t^{o} + \epsilon_{it}^{o} \tag{3.4}$$

Where ϵ_{it}^{o} is the residuals and meets the moment condition

$$E(\epsilon_{it}^{o}|TENSYS_{it}, \omega_{it}, \eta_i^{o}, \tau_t^{o}) = 1 \tag{3.5}$$

Therefore, controlling for ϵ_{it}^{o} in equation (3.1) sufficiently removes the endogeneity bias.

$$E(EnvPat_{it}|x_{it}, \omega_{it}, \eta_i, \tau_t, \epsilon_{it}^{o}) = \exp(\alpha x_{it} + \beta\omega_{it} + \eta_i + \tau_t + \rho\epsilon_{it}^{o}) \tag{3.6}$$

As a rule-of-thumb, I present the exogeneity test -Durbin-Wu-Hausman test- results for the joint significance of the residuals in equation (3.6).

3.4. Results

Environmental Policies, Institutions and Environmental Patents

Table 3.1. Environmental Policies, Institutional Quality and Environmental Patents

Dep. Var. Env. Patents	(1)	(2)	(3)	(4)	(5)	(6)
Method	Poisson	Poisson	Poisson	Negative Binomial	Negative Binomial	Negative Binomial
EPS	0.560***	0.521***	1.273***	0.255*	0.298**	0.893**
	(0.153)	(0.098)	(0.428)	(0.143)	(0.127)	(0.443)
R&D	0.342***	0.409***	0.452***	0.244***	0.265***	0.280***
in log.	(0.126)	(0.122)	(0.135)	(0.075)	(0.070)	(0.071)
GDP p. c.	-0.389	-0.702**	-0.890**	0.683***	0.486**	0.407
in log.	(0.353)	(0.331)	(0.351)	(0.207)	(0.228)	(0.261)
GHG (kt)	0.521***	0.504***	0.460***	0.629***	0.632***	0.605***
in log.	(0.121)	(0.111)	(0.115)	(0.123)	(0.121)	(0.126)
Bureaucratic q.		0.600***	1.339***		0.302*	0.703**
		(0.163)	(0.388)		(0.180)	(0.282)
EPS*Burea.q.			-0.219*			-0.169
			(0.125)			(0.117)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	687	686	686	687	686	686

Notes. Standard errors are clustered by country. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3.1 presents the basic results. Columns 1-3 report Poisson regressions and columns 4-6 report Negative Binomial regressions. Across all the columns of

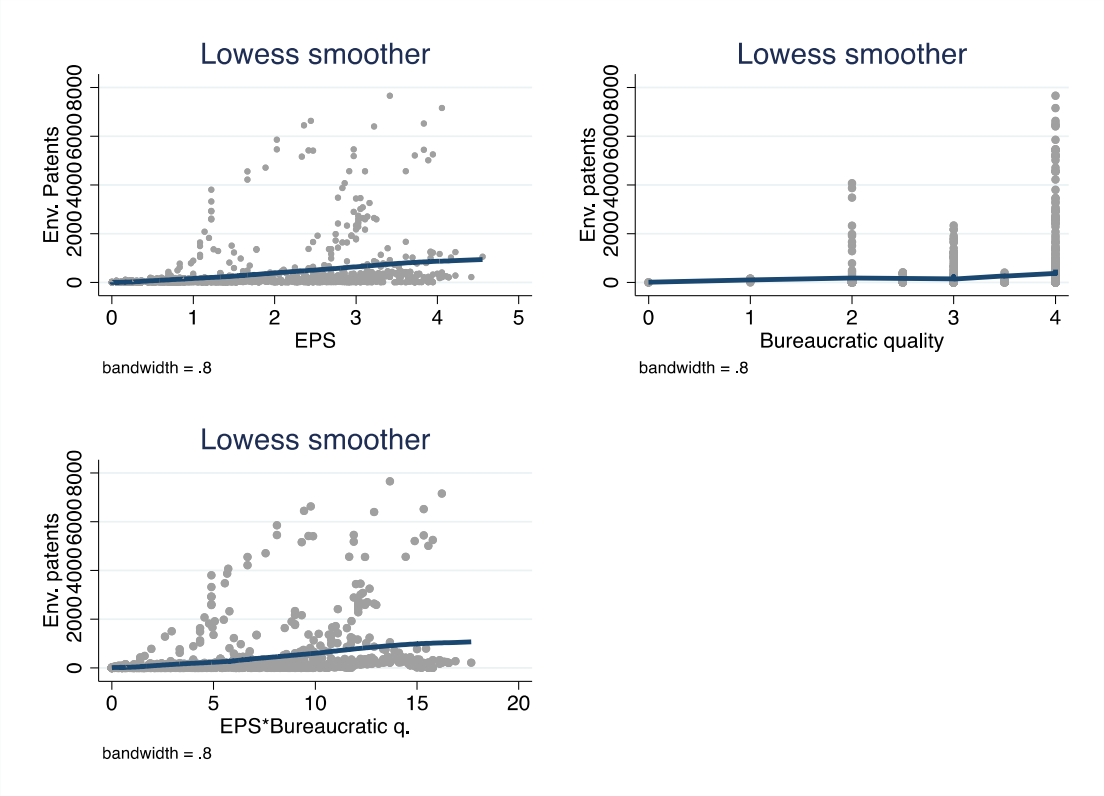
Table 1, the coefficient on EPS lies between 0.255 and 1.273. A coefficient of 0.52 indicates that 10% increase in EPS (e.g., from the mean of 1.8 to 1.98) leads to 5.2% increase in the probability of gaining additional patents (e.g., from the mean of 329 patents to 346). This result is both economically as well as statistically significant.

All columns control for R&D spending in renewable energy, GDP per capita, GHG emission in kt, time dummies and fixed effects[25]. As expected, R&D has a positive and significant association with environmental patents across models. Columns 1 and 4 contain only environmental policy, then I add institutional variable, bureaucratic quality, into columns 2 and 5. Having institutions in the regression slightly decreases the coefficient of EPS from 0.589 to 0.551. And the coefficient on bureaucratic quality is also highly significant, suggesting that the institutional strength to absorb shocks and minimize policy revision during the government change is essential as much as stringency of environmental policies. Lastly, I include the interaction term between policy and institutions in columns 3 and 6 to measure their joint effect. While the interaction term alone has a positive and significant effect[26], together with EPS and bureaucratic quality it does not necessarily show an impact. In overall, consistent with the bivariate relationships in Figure 6 there is a positive and significant association between EPS, institutions, interaction term and environmental patents.

[25] PSM fixed effects are not significant in Poisson while significant in Negative Binomial. When I disregard the fixed effects, the qualitative results are very similar. Fixed effects slightly reduce the marginal effects of EPS and institutions from 0.56 to 0.52 and from 0.76 to 0.60 respectively.

[26] Coefficient on the interaction term is significant and positive both in Poisson and Negative Binomial regressions when it is included alone, without EPS and institutions.

Figure 3.5. Nonparametric Regression on Environmental Patents and (i) EPS, (ii) Bureaucratic Quality, and (iii) Their Joint Effect.



Source: Author

3.4.1. Some Basic Robustness Checks

Carbon pricing. I add various measures of environment-related taxes into the baseline specification, including environment, energy, pollution, transportation, and resource taxes. Table 3.2 presents the results. Except for the resource taxes, all types of environment-related taxes have a significant and positive impact on environmental patents. Thus, findings support the induced innovation hypothesis (Popp, 2022) at the country level that increased carbon pricing makes countries to increase innovation in clean technologies. Natural resources such as the solar and wind energy are used for renewables, so their taxes may not necessarily cause to a

rise in green innovation due to the increased costs. Including energy prices into the baseline model does not sharply change coefficients on EPS and institutions.

Table 3.2. Induced Innovation

Dep. Vr. *Env. patents* Type of tax	(1) Environmental tax	(2) Energy tax	(3) Pollution tax	(4) Transportation tax	(5) Resources tax
Bureauc. q.	0.306	0.236	0.536***	0.349*	0.519*
	(0.187)	(0.187)	(0.100)	(0.204)	(0.265)
EPS	0.253**	0.154	0.288**	0.346***	0.440***
	(0.118)	(0.129)	(0.124)	(0.114)	(0.150)
Taxes	0.151***	0.181***	0.101*	0.113**	0.011
in log.	(0.050)	(0.049)	(0.052)	(0.048)	(0.036)
R&D in renew.	0.269**	0.284***	0.370***	0.273**	0.425***
in log.	(0.112)	(0.109)	(0.099)	(0.115)	(0.113)
GDP p. c.	-0.233	-0.096	-0.182	-0.399	-0.445
in log.	(0.407)	(0.399)	(0.377)	(0.406)	(0.515)
GHG (kt)	0.369***	0.333***	0.551***	0.401***	0.605***
in log.	(0.074)	(0.076)	(0.121)	(0.077)	(0.150)
Observations	506	505	434	507	389

Notes: Standard errors are clustered by country. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Kyoto ratification. Signing the Kyoto agreement stimulated the efforts for tackling climate change. Since the correlation between Kyoto dummy and EPS is high (see

Table A3.3 in Appendix), I do not include Kyoto in the baseline estimation. Rather, I present results separately in Table 3.3. As expected, Kyoto ratification is significant determinant of countries' innovative activities in environment-friendly technologies. Inclusion of Kyoto dummies does not change the impact of EPS and institutions. It only slightly reduces the magnitudes of coefficients (from 0.52 to 0.40 and from 0.60 to 0.55 respectively).

Table 3.3. Kyoto Ratification and Environmental Patents

Dep. Var. *Env. patents*	(1) Baseline	(2) Add Interaction	(3) Add Env. taxes
Bureaucratic q.	0.554***	1.468***	0.208
	(0.152)	(0.384)	(0.161)
EPS	0.397***	1.314***	0.091
	(0.101)	(0.445)	(0.111)
Kyoto	0.497*	0.556**	0.563*
	(0.289)	(0.278)	(0.329)
R&D	0.403***	0.458***	0.269**
in log.	(0.125)	(0.141)	(0.143)
GDP p. c.	-0.446	-0.674*	0.079
in log.	(0.390)	(0.391)	(0.407)
GHG (kt)	0.581***	0.530***	0.449***
in log.	(0.149)	(0.150)	(0.120)
EPS*Burea.Q.		-0.273**	
		(0.124)	
Env. tax			0.154***
in log.			(0.042)
Fixed Effects	Yes	Yes	Yes
Observations	686	686	625

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. ***

Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Triadic Patents. Alternatively, I can use the environmental patents signed under a specific patent family, called Triadic Patent Family, which represents the patent applications filed under the three largest markets: European, Japanese and US patents offices (EPO, JPO, USPTO).

Table 3.4. Triadic Patent Family

Dep. Var. Env. patents	(1) Baseline	(2) Adding Kyoto	(3) Adding Env. Taxes	(4) Adding Interaction
EPS	0.744***	0.673***	0.032	0.882**
	(0.230)	(0.191)	(0.156)	(0.352)
Bureaucratic q.	0.620***	0.605***	0.078	0.854**
	(0.178)	(0.174)	(0.179)	(0.417)
R&D	0.257	0.261	0.151	0.176*
in log.	(0.171)	(0.170)	(0.192)	(0.098)
GDP p. c.	-1.100***	-1.017***	0.303	0.199
in log.	(0.322)	(0.325)	(0.370)	(0.412)
GHG (kt)	0.577***	0.602***	0.419***	0.384***
in log.	(0.202)	(0.220)	(0.193)	(0.118)
Kyoto		0.250	0.569	0.613**
		(0.226)	(0.249)	(0.262)
Env. tax			0.230***	0.238***
in log.			(0.049	(0.048)
EPS*Bureau.Q.				-0.243**
				(0.098)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	684	684	624	624

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Coefficients on EPS and institutions are still consistent with the baseline findings (Table 3.4). To produce frontier innovations in terms of environment-friendly technologies, countries with more stringent policies and bureaucratic quality perform better. Only R&D and Kyoto lose their significance that is in line with Nesta et al.'s (2014) results for triadic patents. Patent offices represent the economic value and technological quality of inventions (Squicciarini et al., 2013). So, insignificant effects of R&D and Kyoto may indicate resource misallocation problem (Nesta et al., 2014). Countries, other than frontiers, may focus on technologies which they do not have an expertise.

R&D in all energy sectors. R&D spending in renewables is used in the baseline estimations. Alternatively, R&D spending in all energy-related sectors are also available. Table 3.5 presents the results when I control for public R&D expenditure in all energy sectors. Coefficients on EPS and institutions are in parallel to the previous models. Differently from R&D in renewables, R&D in all energy sectors show a significant and positive impact for triadic patents as well. R&D in renewables may not be enough for frontier technologies whereas R&D in all energy sectors catch the correct technologies. Kyoto ratification still does not influence triadic patents. Including the interaction term between policy and institutions captures the effect of EPS on environmental patents. Without the interaction term, individual effect of EPS is still visible.

Table 3.5. R&D Spending in All Energy Sectors

Dep. Var. Env. patents	(1)	(2)	(3)	(4)
Patent family	PTC	PTC	Triadic	Triadic
EPS	0.551***	0.166***	0.635***	0.148*
	(0.107)	(0.094)	(0.223)	(0.088)
Bureaucratic q.	0.549***	0.173	0.688***	-0.034
	(0.189)	(0.190)	(0.192)	(0.233)
R&D	0.220**	0.086	0.330***	-0.076
in log.	(0.096)	(0.125)	(0.114)	(0.106)
GDP p. c.	-0.596	0.154	-0.957***	0.455
in log.	(0.376)	(0.451)	(0.314)	(0.356)
GHG (kt)	0.589***	0.574***	0.481**	0.547***
in log.	(0.137)	(0.146)	(0.206)	(0.160)
Kyoto		0.584*		0.470*
		(0.326)		(0.250)
Env. tax		0.153***		0.249***
in log.		(0.050)		(0.043)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	674	500	672	498

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Political risk rating. In addition to the bureaucratic quality, ICRG provides a comprehensive index called political risk rating (PRR). In Table 3.6, I replace the bureaucratic quality with PRR. First, coefficients on EPS, renewables' R&D, crude oil prices and Kyoto are like the previous models. An interesting result from Table 3.6 is that the individual effect of PRR is not consistent across models. The robust impact of the bureaucratic quality index can be compensated by other components of PRR. On the other hand, the joint effects of environmental policies and political

risk rating is significant and positive for both all patents and triadic patents. While bureaucratic quality is individually a determinant of environmental patents, environmental policies need less risky political environment to increase its impact.

Table 3.6. Political Risk Rating

Dep. Var. Env. patents	(1)	(2)	(3)	(4)
Patent Family	PTC	PTC	Triadic	Triadic
EPS	0.541***	0.053	0.706***	0.018
	(0.140)	(0.102)	(0.243)	(0.093)
Political risk r.	0.025*	0.006	0.023	0.005
	(0.013)	(0.013)	(0.017)	(0.013)
R&D	0.370***	0.253***	0.190	0.142*
in log.	(0.129)	(0.113)	(0.174)	(0.083)
GDP p. c.	-0.592*	0.186	-1.001***	0.320
in log.	(0.341)	(0.402)	(0.353)	(0.379)
GHG (kt)	0.527***	0.438***	0.573***	0.415***
in log.	(0.118)	(0.120)	(0.221)	(0.123)
Crude oil		0.171***		0.235***
		(0.036)		(0.045)
Kyoto		0.608*		0.565
		(0.336)		(0.252)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	686	506	684	504

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3.7. Market vs. Nonmarket Environmental Policies and Patents

Dep. Var. *Env. patents*	(1)	(2)	(3)	(4)	(5)	(6)
EPS type	Market	Market	Market	NonMark.	NonMark.	NonMark.
Market EPS	0.298*	-0.141*	0.770*			
	(0.156)	(0.078)	(0.426)			
Nonm. EPS				0.182**	0.075	0.681***
				(0.083)	(0.072)	(0.197)
Bureaucratic q.	0.814***	0.090	0.504**	0.669**	0.185	1.014***
	(0.299)	(0.150)	(0.237)	(0.325)	(0.153)	(0.266)
R&D	0.578***	0.283**	0.294**	0.634***	0.294**	0.308**
in log.	(0.098)	(0.120)	(0.123)	(0.103)	(0.118)	(0.120)
GDP p. c.	-0.945**	0.269	0.171	-0.887*	0.092	-0.036
in log.	(0.450)	(0.374)	(0.392)	(0.463)	(0.385)	(0.410)
GHG (kt)	0.348***	0.343**	0.321**	0.267***	0.422***	0.418***
in log.	(0.120)	(0.151)	(0.155)	(0.076)	(0.123)	(0.123)
Env. tax		0.189***	0.189***		0.165***	0.153***
in log.		(0.040)	(0.037)		(0.034)	(0.033)
Kyoto		0.632**	0.593*		0.553*	0.587*
		(0.299)	(0.304)		(0.315)	(0.309)
M.EPS*Bur.Q.			-0.242**			
			(0.120)			
NonM.EPS*Bur.Q.						-0.165***
						(0.051)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	686	506	506	686	506	506

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Market vs. Non-market EPS. I also compare effects of environmental policies as distinguished by market vs. nonmarket policies (Table 3.7). Both market and

nonmarket EPS have a positive and significant effects on environmental patents while the magnitude of the coefficient on market EPS is higher than nonmarket EPS' (0.298 vs 0.182). Their significance disappears when Kyoto dummy is included in the regression. Bureaucratic quality is still significant determinant of innovation while its joint effects with policies do not necessarily cause to better performance in environmental patents.

Table 3.8. Including Population and per Capita Values

Dependent vr:	# of env. patents	# of env. patents	Env. patents p. capita
Bureauc. q.	0.600***	0.702***	0.593**
	(0.163)	(0.195)	(0.272)
EPS	0.521***	0.468***	0.233*
	(0.098)	(0.108)	(0.128)
R&D	0.409***	0.356***	
in log	(0.122)	(0.118)	
GDP p. c.	-0.702**	-0.375	0.090
in log	(0.331)	(0.286)	(0.227)
GHG (kt)	0.504***	0.160	
in log	(0.111)	(0.304)	
Population		0.484	-0.033
in log		(0.344)	(0.112)
R&D capita			0.300***
in log			(0.108)
GHG capita			-0.010
in log			(0.223)
Observations	686	686	686

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Including population and per capita values. Lastly, I include population as a control variable as well as per capita values of all independent variables. Since the dependent variable is count data, per capita values can make a difference in the results. Table 3.8 presents the findings. Column 1 is the baseline results. Column 2 adds population as control. Including population cause a slight decrease on magnitude of policies but not a change on significancy. Population itself has not impact on patents. Column 3 replaces variables with per capita values. While significancy and coefficient on policies decreases, the impact is still visible. R&D as well as bureaucratic quality are still significantly effective. Population is still not significant.

Overall, these results provide robust results for positive effect of policies and institutions on innovation.

3.4.3. Instrumenting the Environmental Policy Stringency

In this section, I consider an instrumental variable strategy to tackle possible endogeneity of environmental policies. I am concerned that the positive correlation between environmental policies and innovation is stemmed from selection. As discussed in Section 3, democratic durability is expected to increase the stringency of environmental policies, so used as a instrument.

Table 3.9 presents results for both first stage and second stage regressions. The first column assumes exogeneity of policy variable and does not control for fixed effects. Column 2 presents the first stage where EPS is regressed on TENSYS and all other controls. As expected, the instrument – democratic durability – is positive and highly significant. One year longer consolidated democracy results in 7% more stringent environmental policies (from mean of 1.78 to 1.9). Column 3 presents the second stage where the control function method is used. Coefficient on

EPS is still significant, and its magnitude is doubled. OLS is biased toward zero that means an attenuation bias due to measurement error. This result suggests that the impact of EPS is underestimated when it is assumed as exogenous.

Table 3.9. Environmental Policies, Institutional Quality and Environment-friendly Patents – Controlling for Endogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent vr.	Env. patents	EPS	Env. patents	Env. patents	Env. patents	Env. patents
Estimation method	Poisson	OLS (1st stage)	Poisson (Control func.)	Poisson (Control func.)	Poisson (Control func.)	Poisson (Control func.)
Sample	All	All	All	All	High str.	Low str.
EPS	0.521***		1.229***	1.297***	1.234***	0.032
	(0.098)		(0.205)	(0.389)	(0.264)	(0.242)
Bureaucratic q.	0.600***		0.439**	0.504	0.517***	0.356*
	(0.163)		(0.179)	(0.399)	(0.181)	(0.200)
TENSYS		0.073***				
		(0.005)				
EPS*Burea.Q.				-0.019		
				(0.094)		
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Exogen. test p.			0.000	0.000	0.000	0.367
Observations	686	683	658	658	395	263

Notes: Standard errors are clustered by country. All columns control for ln(GDPc), ln(GHG), R&D, and time dummies. TENSYS is the time length for democratic institutions. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. Exogeneity test at the second stage is Durbin-Wu-Hausman test for the coefficient on residuals from the first stage. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Next, Column 4 includes the interaction term between EPS and bureaucratic quality and repeat the model in Column 3 of Table 1. The interaction has no effect on patents even when EPS is treated as endogenous. Therefore, significancy of the

interaction term at 10 percent level in Column 3 of Table 1 is a biased result. Last two columns of Table 3.8 divide the sample into countries with high and low stringency of environmental policies by the mean value. While the EPS is highly and economically significant in countries with high stringent policies, its affect disappears in countries with low stringent policies (and the instrument is significant in both first stages). This suggests that countries should exceed a threshold to benefit from environmental policies in terms of innovative outcome.

3.5. Concluding Remarks

Given the importance of innovation in tackling climate change, it is important to understand institutional determinants of environment-friendly innovation at the country level. This paper attempts to estimate the relationship between environmental policies, political institutions, and environmental patents.

In support of existing literature, more stringent policies boost innovation. The evidence from democratic durability as an instrument suggest that this result stem from endogenous selection. In addition to policies, scholars remind the need for institutions while implementing green industrial policies, so bureaucratic quality facilitates innovation. Their positive effects are robust to controlling for R&D spending. Alternative models are also consistent with these baseline findings. Moreover, Kyoto ratification stimulated countries' efforts to environment-friendly innovation, as expected. In line with the induced innovation hypothesis, environmental taxes -including energy, pollution, and transportation- cause to more innovation in environment-friendly technologies.

This study has implications for countries. While environmental policies are required to increase innovation in green technologies, the institutional environment

has also essential role for successful implementation of these policies. Bureaucratic quality demonstrates a country's ability to adopt to government changes by minimizing policy revision. Indeed, environmental policies need long-term commitment to reach an effective outcome. However, especially democratic governances are subject to change in the short-term. Therefore, how a country absorbs shocks during the change will determine the effectiveness of environmental policies and bring in green innovation.

This study also has some limitations. It uses the stringency of environmental policies rather than specific policy indices such as feed-in-tariff, carbon taxes, portfolio standards, etc. It would be helpful for governments to observe the impacts of specific policy types while determining the next environmental policy targets. Furthermore, despite the estimations with alternative variables, models can still suffer from omitted variable bias which affect the interpretation of causality from policies, and institutions to innovation. Yet, I believe that the results are unsusceptible to such bias because pre-sample mean correctly captures any potential country specific and time-invariant characteristics. Nevertheless, further research can be done in more comprehensive way, for instance, with the inclusion of path-dependency in green innovation.

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Appendix

Table A3.1. List of Countries.

Australia	Finland	Korea	Slovak Republic
Austria	France	Luxembourg	Spain
Belgium	Germany	Mexico	Sweden
Brazil	Greece	Netherlands	Switzerland
Canada	Hungary	New Zealand	Turkey
Czech Republic	Ireland	Norway	United Kingdom
Denmark	Italy	Poland	United States
Estonia	Japan	Portugal	

Table A3.2. Summary Statistics.

Variables	Obs.	Mean	Std. dev.	Min.	Max.
Env. patents (PTC)	1,160	329.55	914.36	0	7662.5
Env. patents (Triadic)	1,150	128.52	386.93	0	3536.4
EPS	1,240	1.78	1.19	0	4.9
Non-market EPS	1,240	2.96	2.006	0	6
Market EPS	1,240	0.98	0.806	0	4.2
Bureaucratic Quality	1,213	3.33	0.79	0	4
Political Risk Rating	1,212	77.12	10.49	35	97
Crude oil import pri.	756	50.27	31.71	11.7	117.8
Electricity price	896	123.79	53.28	17.8	285.16
Kyoto dummy	1,240	0.58	0.49	0	1
(ln) R&D renewables	741	17.17	1.825	9.1	21.7
(ln) R&D all energy	730	18.98	1.77	14.6	23.2
(ln) GDP p.capita	1,210	9.91	1.017	6.3	11.63
(ln) GHG	1,200	12.19	1.65	7.9	16.36

Table A3.3. Correlation Matrix.

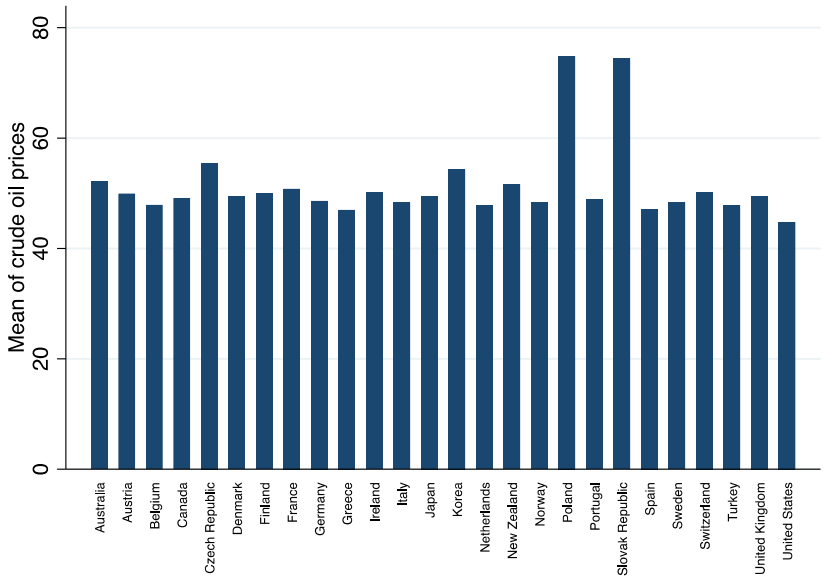
	Env. patents	EPS	Bureauc q.	Crude oil	Kyoto dummy	R&D ren.	GDP p. cap.	GHG
Env. patents	1.0000							
EPS	0.232	1.0000						
Bureauc q.	0.165	0.012	1.0000					
Crude oil	0.209	0.666	-0.067	1.0000				
Kyoto d.	0.031	0.713	-0.0930	0.688	1.0000			
R&D ren.	0.598	0.515	0.218	0.309	0.198	1.000		
GDPc	0.166	0.320	0.754	0.1310	0.137	0.425	1.000	
GHG	0.617	-0.042	-0.026	-0.029	-0.169	0.611	-0.074	1.000

Table A3.4. Induced Innovation – Electricity and Crude Oil Prices

Dep. Var. Env.Patent	(1)	(2)	(3)	(4)
Energy price type	Crude oil	Crude oil	Electricity	Electricity
Bureaucratic q.	0.526***	0.931**	0.542***	0.928***
	(0.171)	(0.400)	(0.195)	(0.334)
EPS	0.276***	0.710*	0.416***	0.826**
	(0.097)	(0.413)	(0.110)	(0.366)
Crude oil pri.	0.012	0.011		
	(0.019)	(0.019)		
Electricity pri.			0.002	0.002
			(0.001)	(0.001)
R&D ren.	0.456***	0.458***	0.390***	0.398***
	(0.152)	(0.153)	(0.138)	(0.141)
GDPc	-1.239***	-1.306***	-0.570*	-0.619**
	(0.396)	(0.418)	(0.311)	(0.313)
GHG	0.401***	0.395***	0.528***	0.523***
	(0.116)	(0.118)	(0.117)	(0.119)
EPS*Burea.Q.		-0.117		-0.112
		(0.106)		(0.099)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	625	625	626	626

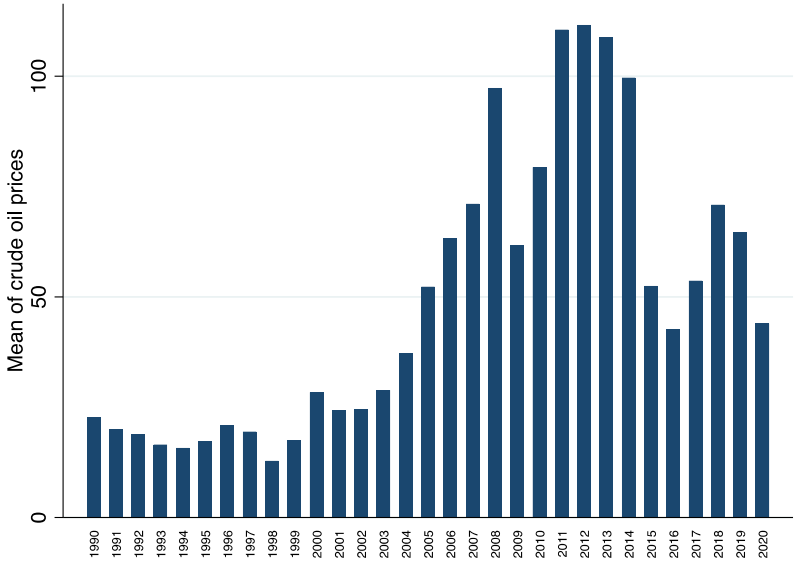
Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure A3.1. Averaged Crude Oil Import Prices by Country



Source: Author

Figure A3.2. Averaged Crude Oil Import Prices by Year



Source: Author

국 문 초 록 (Abstract)

경제 및 녹색 혁신에 대한 에세이:

공적개발원조, 연구개발 및 환경 정책의 역할

본 논문은 경제 복잡성(economic complexity)과 녹색 혁신(green innovation)에 영향을 미치는 다양한 요인들의 역할을 이해하는 것을 목표로 하며 이를 실증적으로 분석하는 세 편의 연구를 수록하고 있다. 첫 번째 연구는 개발도상국에 있어 가장 큰 자본 흐름 중 하나인 국제원조(foreign aid)에 초점을 맞추며, 두 번째 연구는 혁신 활동을 측정하는 일반적인 척도인 연구개발(R&D) 지출과 특허 등록 현황을 비교한다. 마지막 세 번째 연구는 청정기술(clean technology)의 개발과 도입의 시의성과 필요성을 고려하여 친환경 특허의 제도적 결정요인을 분석한다.

먼저, 대외원조에 중점을 둔 첫 번째 연구는 타국 또는 기관의 지원이 수원국의 생산 능력에 미치는 영향을 살펴보기 위해 2003년에서 2019년 사이에 원조를 받은 86개국에 대한 패널 데이터에 기반하여 최근 국가의 생산성을 대리하는 지표로 주목을 받는 경제 복잡성 지수(Economic Complexity Index)를 대외원조와 연관시켜 분석하였다. 경제 복잡성 지수는 미래 성장에 대한 예측을 가능하게 하여 대외원조의 효과를 가늠하는 데 유용하다. 연구 결과에 따르면 대외원조는 수원국의 경제 복잡성에 도움이 되는 것으로 나타났다. 그러나 분야별 원조 활동(sectoral aid)의 효과에 대해서는 엇갈린 결과가 도출되었다. 무역 개방과 해외직접투자(FDI)는 역시 개발도상국의 경제 복잡성에 영향을 미치는 요인으로 확인되었다.

이어지는 두 번째 연구에서는 1996~2017년 기간과 102개국을 포괄하는 패널 데이터를 사용하여 R&D 지출과 특허가 경제 복잡성 지수에 미치는 영향을 분석함으로써 혁신 활동의 측정을 더 잘 대리하는 지표가 무엇인지에 관한 학술적 논의에 기여하였다. 연구 결과, R&D 지출은 다른 지표보다 경제 복잡성과 하위 샘플을 이용한 추정에 있어 매우 높은 강건성을 보였다. 이에

비해 특허는 본 연구에서 살펴본 모든 모델에서 상대적으로 작은 영향과 낮은 강건성을 가졌다. 경제 복잡성은 체화된 지식(embedded knowledge)과 기술의 수준을 나타내기 때문에, 새로운 지식을 창출하는 능력을 가진 R&D가 암묵지(tacit knowledge)의 축적보다 가시적인 결과를 보여주는 특허보다 더 나은 지표가 될 수 있음을 확인하였다.

마지막으로 세 번째 연구는 1990~2019년 기간 중 31개국의 데이터를 포함하는 패널 데이터를 사용하여 환경 정책이 친환경 기술의 특허 등록에 미치는 영향을 분석하였다. 이 패널 데이터는 카운트 데이터(count data)이므로 이를 분석하기 위해 포아송(Poisson) 회귀모형을 사용하였으며, 국가별 고정효과(country fixed effects)를 통제하고 국가 간 이질성을 다루기 위해 모평균 추정량(pre-sample mean estimator)을 사용하였다. 연구 결과에 따르면, 국가적 차원에서 석유와 전기의 가격을 높이는 것이 꼭 녹색 혁신의 증가로 이어지지는 않으나, 환경세의 도입은 유발적 혁신 가설(induced innovation hypothesis)을 따르며 녹색 혁신을 증가시키는 것으로 나타났다. 또한, 더욱 까다로운 정책과 단단한 제도적 기반을 가진 국가일수록 친환경 기술에 대한 혁신 활동을 더 잘 수행하는 것으로 확인되어 기후변화에 대처하려면 정부의 개입이 필요하다는 주장에 힘을 실었다. 마지막으로 통제함수접근법(control function approach)과 도구변수(instrumental variable)를 이용하여 환경정책과 특허 간의 인과관계를 확인하였다. 본 연구는 녹색 혁신에 있어 제도의 수준이 미치는 영향을 분석함으로써 기존 연구를 확장했다는 의의가 있다.

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주요어: 경제 복잡성, 녹색 혁신, 국제원조, 연구개발, 특허 등록, 환경정책
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