

Arbeitspapiere des Osteuropa-Instituts
Arbeitsbereich Politik

Shilong Zhang

Energy Resources, Discovery, and
Green Transformation.
Evidence from the Post-Soviet Space

99/2025

Freie Universität Berlin

Energy Resources, Discovery, and Green Transformation. Evidence from the Post-Soviet Space

About the author:

Shilong Zhang
Freie Universität Berlin
aheirqq.com@gmail.com

Abstract:

This paper examines whether giant oil and gas discoveries hinder the green transformation in post-Soviet space. Post-Soviet countries share a similar historical background but have pursued drastically different energy strategies, providing an ideal field to observe the influence of resource discoveries by minimizing the unobservable variables. Treating giant resource discoveries as natural experiments, it evaluates both short-term and long-term causal effects on the green transformation measured in four dimensions: total energy supply (TES), energy mix, energy efficiency, and international investment in renewables. The findings reveal that giant discoveries lead to a short-term decline in TES, fossil energy supply, and renewable energy supply; better (political) institutions deepen this short-term decline, while stronger economic institutions increase TES and renewable energy (excluding biofuels). However, these effects are short-lived. In the long term, discoveries result in increased TES and fossil energy supply, reduced renewable energy supply, and worsening energy efficiency. These results support the resource curse theory, showing that institutional quality moderates short-term disruptions but cannot prevent long-term fossil fuel dependence. The thesis contributes to the limited literature on the direct impact of resource discoveries on energy transition in post-Soviet countries and highlights the need for institutional strengthening and targeted international support in renewables in countries with recent resource shocks.

Keywords:

Giant resource discoveries, green transformation, post-Soviet countries, resource curse, natural experiments, institutions.



Arbeitspapier 99/2025

Abteilung Politik am Osteuropa-Institut der Freien Universität Berlin

Shilong Zhang

Energy Resources, Discovery, and Green Transformation Evidence from the Post-Soviet Space

Shilong Zhang (2025) Energy Resources, Discovery, and Green Transformation. Evidence from the Post-Soviet Space. Arbeitspapiere des Osteuropa-Instituts (Abteilung Politik) 99/2025 Freie Universität Berlin 2025.

Impressum

© bei den AutorInnen

Arbeitspapiere des Osteuropa-Instituts, Freie Universität Berlin

Abteilung Politik

Garystraße 55

14195 Berlin

Redaktion: Alexander Libman

alexander.libman@fu-berlin.de

Lektorat/Layout: Alexander Libman

Table of Contents

List of abbreviations/notations	3
List of tables	5
List of figures	5
Introduction	6
1. Literature review: The impact of resource discovery	7
1.1. Resource discovery in a macroeconomic model	8
1.2. Resource curse and expectation-induced resource curse.....	9
1.3. Resource discovery: a new proxy for resource.....	11
2. Different energy strategies in the post-Soviet space	16
2.1. Fossil energy country.....	18
2.2. Green transforming country.....	22
2.3. Hydropower country	24
3. Theoretical framework and methodology	26
3.1 Theories and hypotheses.....	26
3.2 Natural experiment	28
4. Empirical strategy and data	31
4.1. Independent variable: giant discovery	32
4.2. Control variable: the quality of the institution.....	33
4.3. Dependent variables	35
5. Results	37
5.1 Energy supply	37
5.2 Energy mix.....	39
5.3 Energy efficiency	43
5.4 Investment in renewables	44
6. Robustness check	46
6.1 Corruption indexes as institutional proxies	46
6.2 Alternative dependent variables.....	47
6.3 Excluding outliers: Russia and the Baltic states	49
Conclusion.....	50
Disclaimer on AI Assistance	52
References	53
Appendix	57

List of abbreviations/notations

- ASPO: Association for the Study of Peak Oil
BCI: Bayesian Corruption Indicator
CAPS: Central Asia Power System
CBIE: Central Bank Independence - Extended Index
CSCI: Comprehensive State Capacity Index
DSGE: Dynamic Stochastic General Equilibrium
EcGI: Economic Globalization Index
EFW: Economic Freedom Summary Index
EUR: Estimated ultimate recovery
FDI: Foreign Direct Investment
FE: Fossil energy
GDP (PPP): Gross domestic product at purchasing power parity
GHG: Greenhouse gas
GRD: UNU-WIDER Government Revenue Dataset
GSD_rl: Global State Dataset, rule of law
GSD_rl_ac: Global State Dataset, rule of law, absence of corruption
GSD_rl_pe: Global State Dataset, rule of law, predictable enforcement
IEA: International Energy Agency
IEF: Index of Economic Freedom
IRENA: International Renewable Energy Agency
LNG: Liquefied Natural Gas
MMBOE: Million barrels of oil equivalent
MTOE: Million tons of oil equivalent
NECP: National Energy and Climate Plan
PLTV_xconst: Polity V, executive constraints
RE: Renewable energy
Re_capa: installed capacity of renewable electricity
Re_exbio: Renewable electricity excluding electricity from biofuels
RE_exbio: Renewable energy excluding biofuels
Re_gene: Renewable electricity generation
SDG: Sustainable Development Goals
SDG_7.2.1: Renewable energy share in the total final energy consumption
SDG_7.3.1: Energy intensity measured in terms of primary energy and GDP
SDG_7.a.1: International financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems
SDG_7.b.1: Installed renewable energy-generating capacity in developing and developed countries (in watts per capita)
SFI: State Fragility Index
STP: São Tomé and Príncipe

TEG: Total electricity generation

TES: Total energy supply

TFC: Total final energy consumption

UNU-WIDER: United Nations University World Institute for Development Economics Research

VD_corr: Varieties of Democracy Dataset Version 13, political corruption index

VD_rl: Varieties of Democracy Dataset version 13, rule of law index

WGI: Worldwide Governance Indicators

WGI_cc: Worldwide Governance Indicators, Control of corruption

WGI_ge: Worldwide Governance Indicators, government effectiveness

WGI_rl: Worldwide Governance Indicators, rule of law

WGI_rq: Worldwide Governance Indicators, regulatory quality

List of tables

- Table 2.1.1. Gas export, import, and production in Uzbekistan from 2017 to 2023
Table 4.1.1. Giant resource discovery in post-Soviet countries from 1991 to 2019
Table 4.2.1. Indicators for the quality of institutions.
Table 4.3.1. Indicators measuring the green transformation
Table 5.1.1. Regression analysis on TES moderated by WGI
Table 5.1.2. Regression analysis on TES moderated by CBIE
Table 5.1.3. Regression analysis on TES Index moderated by VD_rl
Table 5.2.1. Regression analysis on FE supply moderated by WGI
Table 5.2.2. Regression analysis on FE supply moderated by CBIE
Table 5.3.1. Regression analysis on energy efficiency (GDP/TES) moderated by CSCI
Table 5.4.1. Regression analysis on the investment in renewable energy (SDG_7.a.1) moderated by the overall quality of institutions, including WGI, SFI, CSCI and GSD_rl
Table 6.1.1. Corruption Indexes
Table 6.2.1. Alternative dependent variables

List of figures

- Figure 2.1. Renewable energy (excluding solid biofuels) share of total energy supply over time.
Figure 2.1.1. Energy dependence in Moldova
Figure 2.1.2. Energy dependence in Ukraine
Figure 2.2.1. The share of biofuels and other forms of renewable energy in the TES in Baltic countries (excluding hydro)
Figure 2.3.1. Kyrgyzstan electricity imports vs. exports
Figure 3.2.1. Classifications of experimental designs
Figure 3.2.2. The time distribution of giant oil and gas discoveries in the world (1868-2019)
Figure 3.2.3. The location of all giant oil and gas discoveries in the world (1868-2019).
Figure 4.1.1. The location of all giant oil and gas discoveries in post-Soviet space (1991-2019).

Introduction

Natural resources have long played a disruptive and transformative role in Eurasia, shaping both economic development and political stability. Starting from Auty (1993), natural resources are often seen as a curse, causing slower economic growth and underdevelopment in developing countries, because resource wealth undermines institutional quality, economic diversification, and equitable income distribution. The relationship between resources and all possible social, political, and economic indicators has been examined again and again. But no agreement on the resource's cursing effect was ever reached.

This research aims to study the effect of oil and gas discoveries on the green transformation of post-Soviet countries using regression analysis in the sense of a natural experiment. Instead of using resource endowment, exportation, the share of GDP, and other traditional proxies for resources, I exploited a relatively new independent variable – resource discoveries, i.e., giant oil and gas discoveries. The mere news of discovery can already cause a series of outcomes. Studying the effect of resource discovery long before the beginning of production will uncover the potential short-term influence of resources, which is introduced by future expectations. This field of study mostly employs global data, and recently, more attention has been placed on specific regions, such as Africa and Latin America, and a few papers have focused on specific countries. However, relevant research on Eurasian countries, represented by the resource-abundant Soviet Union and its successors, is blank. Besides, many researchers using global datasets have excluded post-Soviet countries because of data limitations.

The central research question guiding this thesis is: **Will a giant resource discovery hinder the green transformation in post-Soviet countries?** To my knowledge, there is no previous paper studying the effect of oil and gas discovery on a country's energy structure. A giant resource discovery will plausibly increase the production, consumption, and export of oil and gas, but its direct influence on the development of renewable energy remains unknown. Countries with abundant petroleum have fewer incentives to conduct energy transformation, but on the other hand, they do have more resources for transformation. Post-Soviet countries share a similar historical background but have pursued drastically different energy strategies. Caspian economies rely much more on gas and oil, while Tajikistan, Kyrgyzstan, and Baltic countries make use of renewable energy extensively. Post-Soviet provides an ideal field to observe the influence of a giant discovery by minimizing the unobservable variables. This paper contributes to the literature by being the first to examine the impact of giant oil and gas discoveries on green transformation, specifically in the under-researched post-Soviet region.

To answer the research question, this paper draws on three theories. The most important theory is the **resource curse theory**. Studies on the impact of resource discoveries usually start from the reflection of traditional resource theory and aim to supplement or reject it. Resource curse refers to the paradoxical phenomenon where developing countries rich in natural resources experience negative economic and social outcomes. From the literature on the resource curse and discovery, I draw the first hypothesis about the short-term effect of a giant discovery:

H_S: In countries with better institutions, giant discoveries will lead to fewer setbacks in green transformation compared to countries with weaker institutions.

To explain the long-term implications, two additional theories are employed. When path dependence leads to unfavorable carbon emissions that could have been avoided through a systematic shift, the phenomenon is termed **carbon lock-in**. A giant resource discovery will trigger carbon lock-in, deepen the tie between the state and the energy sector, as well as solidify the fossil energy interest group. According to the **green paradox**, green policies will not only not contribute to emission reduction, but accelerate it. Because of facing environmentally friendly policies, resource owners will extract their resources even faster, in anticipation of a threatened energy market in the future. A giant discovery will incentivize them to boost production to maximize their current revenues. Both theories suggest a reinforcing reliance on fossil fuels and a reduction in the urgency or incentive to invest in renewables. Therefore, I put up with the second hypothesis about the long-term effect of a giant discovery:

H_L: Countries with previous resource discoveries will experience a worsening in green transformation in the long term, compared to countries without recent resource discoveries.

Methodologically, this study treats giant oil and gas discoveries as natural experiments. Controlling for time and country fixed effects, giant gas and oil discoveries with estimated ultimate recovery (EUR) reserves greater or equal to 500 million barrels of oil equivalent (MMBOE) can be seen as natural experiments. Giant discoveries are rare and unpredictable, providing a causal framework. According to the dataset, Giant oil and gas field discoveries 2018, there are 18 giant discoveries in post-Soviet countries after its dissolution (Cust et al., 2021). Valid country-year observations are 17 since Russia had 2 discoveries in 2000. The green transformation is measured through four dimensions, namely total energy supply, energy mix, energy efficiency, and the investment in the energy sector. Data is mainly extracted from the International Energy Agency (IEA) and the International Renewable Energy Agency (IRENA). Data on institutional qualities is synthesized from a wide range of datasets.

The paper is structured as follows: Chapter 1 reviews the literature on resource discovery and introduces the resource curse. Chapter 2 outlines the energy strategies of post-Soviet countries, providing necessary background. Chapter 3 elaborates on the theoretical frameworks, presents the hypotheses, and justifies the use of discovery events as natural experiments. Chapter 4 explains the empirical strategy and provides a detailed description of the data. Chapter 5 presents the regression results, followed by Chapter 6, which discusses robustness checks. Finally, in the Conclusion, I summarize the key findings, outline limitations, and suggest avenues for future research.

1. Literature review: The impact of resource discovery

The study of resource discovery unfolded in two relatively separate lines. Scholars have approached it from the macroeconomic perspective and, more recently, from the perspective of the resource curse.

1.1. Resource discovery in a macroeconomic model

Studies of the impact of discovery first came into sight in the 1980s. The discovery of oil in the North Sea in the 1960s stimulated the interest of U.K. economists in the effect of resource discoveries on an open economy. A considerable amount has then been written concerning the macroeconomic impact of resource discoveries in a macroeconomic model, i.e., a small open economy (Buiter & Purvis, 1983; Eastwood & Venables, 1982; Lawler, 1991; Mansoorian, 1991; Neary & Vanwijnbergen, 1984; Spencer, 1984). In this stream of research, attention is exclusively on the relation of discovery and real exchange rate, i.e., Dutch disease.

Buiter and Purvis (1983) identified two kinds of oil shocks - the unanticipated change in the world price of oil and the unanticipated discovery of domestic oil. An oil discovery will worsen the competitive position of the non-oil goods. Increases in known domestic oil reserves can have a transitional negative effect on manufacturing output, even for a net oil exporter. However, there may be shifts in the composition of non-oil goods, probably out of manufacturing into non-traded services, for which they cannot conclude that total employment and the value of total non-oil production would fall. Eastwood and Venables (1982) employed a model with similar assumptions to Buiter and Purvis (1983), but Buiter and Purvis paid more attention to the impact of “the unanticipated oil price change” and had different approaches to analyzing, making comparison difficult. Eastwood and Venables (1982) showed that with the key additional postulate of a time lag between the resource discovery and the spending of the resource revenue, a deflationary interval will follow the initial exchange rate appreciation, confirming the notion that a resource discovery does not pose special problems of macroeconomic management in a properly constructed macroeconomic model which employ the full set of New Classical postulates. They believe that the contractionary effect of the exchange appreciation following the oil discovery only moderates but can in no case outweigh the expansionary effect of the oil-generated spending. Therefore, no recession can arise. Spencer (1984, p. 643) also concluded that “the direct monetary effect of increasing expenditures provides a significant offset to the indirect exchange rate effect stressed by Eastwood and Venables (1982)”. The finding of Mansoorian (1991) echoes those of Eastwood and (Eastwood & Venables, 1982). In the short run, there will be a sharp increase in aggregate expenditure, causing a real appreciation and deindustrialization as in standard Dutch Disease models, because a capital-intensive resource discovery will shift income away from labor to asset holders; Over time, however, as the discovered resources are consumed, the country’s net foreign asset position will deteriorate, decreasing aggregate expenditure. This will cause a long-run real depreciation, a contraction of the non-traded sector, and then release enough factors for the manufacturing sector to cause a pro-industrialization. Thus, the long-run response of the economy to a resource discovery may be the opposite of the conventional view in the Dutch Disease literature.

Neary and Vanwijnbergen (1984) challenged the conclusion of Eastwood and Venables (1982) by pointing out that it is difficult to conceive a situation in which an oil discovery would raise spending but leave money demand permanently unaffected. “The root of the problem is that the direct wealth effect of higher oil wealth increases the demand for money, which, given the nominal money supply, subjects the economy to a contractionary shock which may be

sufficiently great to offset the direct expansionary effects of the oil discovery on domestic spending" (Neary & Vanwijnbergen, 1984, p. 394). However, Lawler (1991) rejected the impact of discovery as contractionary. He used a more detailed specification of the supply side of the economy than his predecessors who adopted a conventional specification of aggregate supply, in which output and employment gravitate back towards their given (i.e., independent of relative prices) natural levels, and found out that the discovery induced an initial contraction in either output or employment, on the contrary, both might increase.

After over 30 years, (Wills, 2019) revised Eastwood and Venables's (1982) result extensively using an extended standard New Keynesian small open economy model in his working paper. He pointed out that their analysis was performed without the benefit of DSGE models. Oil discoveries will, in fact, cause the real exchange rate to appreciate twice: immediately as households learn they are wealthier and consume more; and it will appreciate the second time when production begins, as the government spends the oil revenues on home goods according to a simple fiscal rule. If monetary policy fails to move with the natural interest rate, for example, under widely-used exchange rate pegs or naive Taylor rules, it can cause a recession because of the forward-looking behavior of households and firms. Harding et al. (2020) confirmed the appreciation before production begins. In their standard, dynamic, small-open-economy model, the appreciation is nearly exclusively driven by the non-tradable component of the real exchange rate, providing direct evidence on the channels central to the theories of the Dutch disease. Interestingly, if interpreting a large discovery as a productivity shock to the tradable sector, their results also support the Balassa–Samuelson effect.

1.2. Resource curse and expectation-induced resource curse

The concept of the resource curse, introduced by Auty (1993), refers to the paradoxical phenomenon where developing countries rich in natural resources experience negative economic and social outcomes. While substantial theoretical and empirical evidence supports this notion, there is no universal consensus on its existence or mechanisms.

Since Adam Smith's *Wealth of Nations*, economists have recognized potential challenges associated with natural resource exploitation. Auty (1993) formally defined the resource curse as the adverse economic and social impacts following a resource boom compared to resource-scarce countries. Sachs and Warner (1995) provided further empirical evidence that there is a negative correlation between natural resource exports and per-capita GDP growth, solidifying the resource curse as a widely recognized economic phenomenon.

Early explanations of the resource curse focused on macroeconomic distortions, such as the Dutch Disease. This phenomenon, detailed by Corden and Neary (1982), Gelb (1988) and Auty (1993), involves the appreciation of exchange rates due to resource exports, which reduces the competitiveness of non-resource sectors. Subsequent studies (e.g., Brahmbhatt et al., 2010; Gylfason et al., 1999; Harding & Venables, 2016; Sachs & Warner, 1995) further elaborated on this mechanism, linking it to reduced growth in resource-rich economies. In the meantime, more and more explanations for the resource curse appeared, including corruption and rent-seeking, civil conflict, and the quality of institutions. Resource wealth incentivizes rent-seeking behavior and corruption, diverting resources away from productive activities (Baland & Francois, 2000; Brollo et al., 2013; Torvik, 2002). Studies such as the one from Treisman (2000) link resource

wealth to widespread corruption, especially in resource-dependent economies. Therefore, resource wealth also influences institutional development, and many scholars argue that the resource curse arises and determined from interactions between resource wealth and institutional qualities. (Bhattacharyya & Hodler, 2010; Boschini et al., 2007; Mehlum et al., 2006; Robinson et al., 2006; Ross, 2004). Furthermore, resource wealth fuels societal conflicts, such as civil wars and political instability (Collier & Hoeffer, 1998, 2004; Humphreys, 2005; Macuane et al., 2018; Ross, 2004).

The mechanisms addressed by the resource literature review have one common point: It is **the resource revenues**, not resource endowment, that causes the resource curse. As summarized by Frynas and Buur (2020), first, resource revenues lead to exchange rate appreciation, reducing the competitiveness of non-resource exports. Resource sectors also attract capital and labor, crowding out other industries and stifling economic diversification. Second, resource wealth reduces incentives for political elites to encourage the development of non-resource sectors and to improve the quality of societal institutions. Third, the capture and allocation of resource revenue induce corruption and are bound to be a fuse for all forms of political violence. Resource wealth often motivates rebel groups and coup attempts while at the same time enabling ruling elites to suppress opposition. Therefore, the transmission path from the resource to the resource curse lies per se in the revenues brought by resources. Does it mean that the resource curse only comes into effect after extraction, i.e., windfall obtained from the resource? The answer is, however, negative.

According to Arezki et al. (2017), economists have long examined how changes in expectations can influence forward-looking behavior, a line of inquiry dating back to early 20th-century economists such as Pigou (1927) and Keynes (1936). Indeed, recent studies have provided empirical evidence that **the mere expectation of resource extraction/windfall** can already cause a multitude of resource curse effects. Vicente (2010) conducted difference-in-difference estimates between São Tomé and Príncipe (STP) and Cape Verde, using the “resource shock” in STP as the treatment. From 1997 to 1999, a series of announcements regarding the exploration of offshore oil in STP were issued, tremendously raising the anticipation of a resource boom, but no discovery was ever confirmed later. Cape Verde, also located in West Africa, is a great control sample that shares the same colonial past and experienced similar economic and political shocks, more importantly, without an oil hype or discovery. Vicente found that the expectation of an oil boom in STP increased corruption, particularly in the case of vote buying and misallocating public resources. Frynas et al. (2017) have also approached STP, though, along with Madagascar. In STP, preliminary planning and exploratory extractive work were carried out, but ultimately no discoveries were made, whereas in Madagascar, the discoveries failed to materialize. However, both countries experienced resource curse effects without experiencing genuine resource windfalls. They pointed out that solely the expectation of a resource boom is enough to bring about the resource curse; Anticipation of future resources may lead to at least some adverse effects on political stability and quality of governance, and significantly greater macroeconomic volatility. Besides, Hayat et al. (2013) argued that higher expectations of future income driven by exogenous factors such as the discovery of oil and an

increase in global demand for natural resources can cause an appreciation of the real exchange rate, signaling an early alarm for “Dutch-disease”.

1.3. Resource discovery: a new proxy for resource

Most of the time, the expectation of a resource boom comes from a more concrete event – **a tangible discovery of resources**. In the 2010s, researchers rediscovered resource discovery as an alternative to typical measurements of natural resources for the demand of exogeneity. Distinguished from studies in the 1980s, this new round of discussions over resource discoveries is not limited to its impacts on the exchange rate in a macroeconomic model anymore, but is merged into the study of the resource curse.

Tsui (2011) is one of the first ones to treat oil discovery as an exogenous shock. He argued that oil production and exports are apparently under the influence of geological constraints and producers' willingness, thus turning to oil discovery. Tsui suggested that major discoveries in one region are usually concentrated within the span of a few years, known as the “peak discovery period”. Therefore, it is possible to aggregate the total amount of oil found in one country to the “peak discovery year” of the respective region, as if it were all discovered in this year. This approach allows him to observe the long-term effect of a “one-time-only” oil discovery. Using data from the Association for the Study of Peak Oil (ASPO) over the sample period 1960-2000, which contains the oil endowment, exploration, discovery, extraction, and oilfield geology of the top 65 oil countries, he showed that for non-democratic countries larger oil discoveries are causally linked to a degrading democracy, the estimated effect is larger with higher-quality oil; oil discovery has almost no effect for democratic countries. Later, Cotet and Tsui (2013b) employed the same estimation strategy with the same sample to examine the relationship between discovery and GDP. Their before-and-after comparison shows that countries that were better-endowed after the “peak discovery year” in their region, i.e., experienced major discoveries, observed better GDP growth, controlling for various independent variables that may also influence GDP growth. Besides, major discoveries also lead to a reduction in infant mortality and a gain in longevity. Cotet and Tsui (2013a), eventually, used the discovery of oil - the value of oil discoveries per capita yearly - directly as the treatment in correlation studies. They found that among the top 62 oil-producing countries over the 1930–2003 period from the ASPO dataset, oil discoveries do not increase the likelihood of political violence either in the short or long run, controlling for the intensity of exploration and other relevant independent variables. Rather, oil discoveries increase military spending in non-democratic countries. Vézina (2021) confirmed the result using a panel of 120 developing countries from 1990 to 2017 and found that arms imports increased by 30%, given a giant oil and gas discovery in the past 5 years; the effect of discoveries on arms imports occurs only in countries with high levels of corruption.

Indeed, it is unsophisticated to aggregate all discoveries in one hypothetical year and to regard that every country's resource discovery trajectory shares a collective regional course, and their garbage can regressions(Cotet & Tsui, 2013a, 2013b; Tsui, 2011) are out of date. However, their pioneer role in exploring the potential of resource discovery in quantitative analysis, to be sure, causal analysis, is exceptionally inspiring.

Following them, Masi and Ricciuti (2019) also used the peak discovery year from the ASPO dataset as an exogenous shock. They conducted a synthetic control method case study and estimated the democracy level of 12 developing countries experiencing the peak in the 1970s or later, if without oil discoveries. They found that the relationship between oil discoveries and democracy is dependent on the initial level of democracy itself: In countries like India and Colombia, which had reached high levels of democracy before experiencing the peak of oil discoveries, the democracy level remains almost unchanged; All other countries, apart from Gabon which had a political reform, were negatively affected by the variation in oil endowment.

In this stream of research, discovery is not treated as an independent and separate incident/event; it is the resource reserve changed by discoveries that plays a role.

Lei and Michaels (2014) quickly challenged the conclusion of Cotet and Tsui (2013a). Cotet and Tsui's assumption for the discovery of oil being exogenous is conditional on exploration intensity because exploration is endogenous and correlated to political stability, institutions, oil prices, etc. To control for it, they used the number of wildcat drillings as a proxy for exploration intensity and exploited propensity score matching estimation. Lei and Michaels (2014) avoided this problem by replacing discovery with **giant discovery**, which is defined as those with estimated ultimate recovery (EUR) reserves greater or equal to 500 million barrels of oil equivalent (MMBOE). The giant discovery is rare, hence exogenous to social and political situations, if controlling for time and country fixed effects. Only one thing is found to be correlated with a giant discovery – previous giant discoveries (in the past 10 years). Thanks to this innovation, Lei and Michaels can get rid of redundant confounding variables and set up a neat specification, only with previous giant discoveries as confounders and previous armed conflicts or coups as interaction terms (moderators). Using the data of 782 giant oil and gas discoveries from 1946 to 2003, their results stand in sharp contrast with those of Cotet and Tsui (2013a): Giant discoveries increase the incidence of internal armed conflict 4-8 years after the discovery, and this increase is driven predominantly by countries with recent histories of political violence (in the past 10 years).

Lei and Michael's (2014) introduction of giant discovery stirred up the enthusiasm of researchers greatly. Academia has then developed different topics with giant discoveries as independent variables and the same empirical strategy in the spirit of Lei and Michaels (2014). First, the giant discovery's influence on the energy production and economy is huge enough to be observed and considered a meaningful event. Second, the giant discovery is rare; the timing and the size of the giant discovery are random, making it arguably exogenous if controlling for country and year-fixed effects. Due to this property, giant discovery overperforms other possible proxies for resources, especially in the aspect of causal analysis. Moreover, the lag between discovery and production brings the possibility to distinguish the effect of a giant discovery from the effect of resources (revenues). Hence, quantitative research on the short-term effect of resources is possible. Arezki et al. (2017) tested the effect of giant discovery on key macroeconomic variables in the first place. They extended the giant discovery dataset by constructing the “net present value” (NPV) of the discovery and found that: After a giant discovery, the current account and saving rate decline for the first five years and then rise sharply during the ensuing years; Investment rises robustly soon after the discovery (driven by

private not public investment), whereas GDP does not increase until after five years; Employment rates fall slightly and remain low for a sustained period. Their estimation of NPV remains at the center of references and was eventually included in the dataset for giant oil and gas field discoveries from 1868 to 2018 (Cust et al., 2021).

The economic impact of resource discovery was studied extensively, including the impact on GDP, government fiscal policy, FDI, economic diversification, and productivity. Many research studies showed no special or positive effect of discoveries on economics, such as Cotet and Tsui (2013b) and Smith (2015). But (Cust & Mihalyi, 2017) saw the hidden side of the discovery and came up with the “presource” curse theory: In countries with weak political institutions, the discovery of resources will lead to economic growth underperformance long before the first drop of oil is produced. They employed all giant oil or gas discoveries from 1988 to 2010 in the world as independent variables and the actual GDP growth rate over the next five years, the forecast GDP growth rate, and the differential (forecast error) as dependent variables. After grouping countries with weak institutions, there is a causal correlation between discovery and under-fulfilled forecast GDP growth, while there is no correlation between discovery and lower actual GDP growth or higher forecast GDP growth. Among countries with strong institutions, there is no evidence of any correlations. This result indicated that countries with giant discoveries will not experience a clear worsening of actual GDP growth but will not live up to expectations, which may explain why post-discovery growth disappointments have gone unnoticed for a long according to Cust and Mihalyi. For example, in Smith’s (2015) study, he found newly resource-rich countries on average experienced a large increase in GDP per capita following extraction that persisted into the long term compared to countries that remained resource-poor throughout, and in the pre-exploitation period there no correlation, indicating that GDP is not directly affected by the discovery of resources. The positive effect of discoveries on GDP found by Cotet and Tsui (2013b) also starts in the first decade after the peak year.

This theory was later tested by qualitative case studies and applied in African countries (Frynas & Buur, 2020; Mihalyi & Scurfield, 2021). Sobrinho and Ruzzante (2022) found a “fiscal presource curse”, which could be seen as a mechanism of the presource curse: Over-optimism induced by discoveries leads to permanently higher government debt and, eventually, debt distress episodes, especially in countries with weaker political institutions and governance. This phenomenon is also documented by Sheng and Zhao (2024), who suggested that net foreign assets initially decrease due to increased borrowing but only start to increase around the fifth year after the discovery, aligning with the intertemporal theory that countries save from temporary income increases but borrow in anticipation of future income. However, the presource curse theory faced increasing pressure of generalization. For example, Cavalcanti et al. (2019) compared Brazil’s municipalities with oil drilling and discoveries to those with drilling but no discoveries. Conditioning on drilling intensity, the discovery could be seen as random, enabling a (quasi-experimental) difference-in-difference approach. The results show that municipalities where oil was discovered had a roughly 30% higher per capita GDP for up to 60 years compared to those in the control group. GDP per capita in services increased, workers relocated to the services sector, and urbanization increased, indicating positive spillover effects among different sectors but not between host and neighboring municipalities.

Noticeably, they first distinguished the role of **onshore and offshore discoveries** by concluding that the onshore discoveries entirely drive the result. A hypothesis is that only onshore production brings a local demand shock for oil companies and workers.

The finding of O'Reilly and Murphy (2017) matches with the results of Arezki et al. (2017) that giant discoveries cause government spending to increase in the short run, but this effect dissipates eventually over a 10-year interval. However, the regressions of Okada and Samreth (2021) showed that there is no direct correlation between discovery and government expenditure. The expansion of government expenditure is more through past discoveries, i.e., a sequence of discoveries in 10 years will increase government expenditure for a short term (around 5 years), the effect is moderated by democracy. Katovich (2024) documented that municipalities in Brazil with offshore discoveries that received an expected windfall enjoyed large increases in per capita revenue and spending 10 years after the first discovery announcement, but public goods provision and economic activity remained stagnant or even worsened.

In line with the increasing government spending, FDI inflows into the oil sector and related industries increase significantly after oil discoveries; even non-extraction FDI inflows increase by 59% after oil and gas discoveries in developing countries and trigger new FDI projects in non-resource sectors such as manufacturing, retail, business services, and construction in two years (Sheng & Zhao, 2024; Toews & Vézina, 2022). Evidence also showed that countries with giant oil and gas discoveries attract 100% more Chinese official financing in the three years following a discovery in the form of non-concessional loans and export credit (Abdelwahed & Ohannessian, 2021). Bhattacharyya et al. (2017) tested the effect of giant discovery (mineral resources and petroleum) on fiscal decentralization and found that giant discovery will decrease the subnational share of total government revenue and expenditure for up to 6 years after the discovery; this fiscal centralization effect is moderated and thus weakened by the country's democracy level. Petroleum discoveries, instead of mineral discoveries, drive the effect. Worth mentioning, they were the first ones to consider the effect of **giant mineral discoveries**. Petroleum is more decoupled from the rest of the economy, while minerals tend to be diffused and linked to the rest of the economy. Therefore, revenue and expenditure decisions in a mineral-rich country could be much more evenly spread. The difference between pointed and diffused resources has been addressed before (e.g., Boschini et al., 2007). Bhattacharyya and Keller (2021) confirmed this possibility by suggesting that oil discovery decreases tax as a share of GDP from the non-resource sector, whereas mineral discovery increases the non-resource sector tax as a share of GDP, indicating a greater connectedness of minerals to the rest of the economy.

Perez-Sebastian et al. (2021) found that giant oil and gas discovery increases tariffs during pre-production years and decrease tariffs in the years to follow, but to a lesser extent, most notably in capital-scarce economies with a relatively dominant tradable sector. This suggests that news about oil discoveries increases protectionism. Alsharif and Bhattacharyya (2019) employed giant discovery to test the effect of giant discovery on economic diversification but found no significant correlation. The only exception is non-resource export concentration 8 years after a giant oil discovery, moderated by institutions. Given a giant discovery, countries with better

institutions/executive constraints will experience a milder non-resource export concentration 8 years after a giant oil discovery. Besides, the giant discovery also has no effect on the structure of employment in the non-resource and manufacturing sectors.

Cust et al. (2019) argued that “discoveries, conditional on exploration drilling, are determined by geology and luck and therefore provide exogenous variation”. By comparing manufacturing firms across districts in Indonesia, they found that windfalls raise wages, output, and employment and lead to aggregate productivity improvements: the least productive firms exit, surviving low-productivity firms improve their labor productivity, and the most productive firms expand their employment, showing signs of resisting Dutch Disease. However, a study using global data concluded the opposite remark (Alsharif & Bhattacharyya, 2024): giant oil and gas discovery reduces growth in manufacturing value added and wages, and brings about manufacturing slowdown episodes. At the same time, the effect on employment is insignificant. Besides, innovation activity at the industry level slows down after a giant discovery across developed and emerging economies, probably due to declining governance quality (Mhuru et al., 2022).

Resource discovery also influences living standards, income, and equality. Smith and Wills (2018) tested the effect of giant discoveries on poverty and rural inequality using night-time illumination data. They found that the giant discovery stimulated illumination and GDP after 6 years. However, the share of the population living in darkness at night did not significantly change, suggesting that the economic growth from oil and discovery was not shared with the rural poor, and regional inequality grew. Mamo et al. (2019) investigated the effects of minerals discovery and production on living standards measured also by night lights, using a panel of district-level data from 42 Sub-Saharan African countries for the period 1992 to 2012. Their results showed that nightlights increase 6 years after the first discovery or 8 years after a giant or major discovery. No spillover of the positive effects beyond the host district was observed, just like in the cases in Brazil (Cavalcanti et al., 2019). However, the effects could still be dependent on the institution’s quality. Evidence from Denmark, the Netherlands, and Norway showed that (Hartwell et al., 2022).

Abdelwahed and Ohannessian (2021) found that a giant resource discovery has an influence on female employment, moderated by Islam prevalence. For a country with a high Islamic prevalence, a giant discovery depresses female employment by approximately two percent over 10 years, while there is a positive or neutral impact in countries with a low to moderate Islamic prevalence. They attribute the negative effect to restrictions on women’s mobility in many Muslim countries. When facing job opportunities that emerge during a boom, female workers are at a disadvantage compared to male workers, who are allowed to travel freely outside the home or to decide where to live.

Last, the political effect of discovery includes corruption, support for the incumbent, and conflict. According to Bhattacharyya and Keller (2021), who studied the heterogeneous effects of minerals and petroleum discoveries on the incumbent’s term in office, mineral discoveries reduce the risk of exiting for the incumbent in non-election years, controlling for democracy; oil and gas discoveries play no role. However, if interacting with democracy, mineral discoveries turn insignificant; in contrast, oil and gas discoveries reduce risk, and the effect is

amplified by bad institutions. This heterogeneity may come from the difference between pointed and diffused resources. They also tried to account for this heterogeneity by military expenditure, but the regression results did not agree. The risk-reducing effect of a mineral discovery takes effect 5-8 years after, perhaps during the construction phase of a mine, and it resurfaces 16 years after discovery through a long dormancy. The risk-reducing effect of petroleum among countries with weak institutions (since its effect is dependent on institutions) appears 11 to 20 years after a giant discovery. Therefore, the effects appear to be induced by resource income rather than expectations. However, a case study in Uganda suggested that oil discoveries caused a meaningful increase in the president's electoral support already in the pre-production period; the result is mainly driven by localities that had previously been most electorally competitive (Paler et al., 2023).

Armand et al. (2020) conducted a stunning large-scale randomized field experiment in Mozambique using a massive discovery of natural gas to test its effect on corruption and civil conflict. Taking advantage of the limited media independence and penetration locally and its poor cognition of the discovery, he randomly assigned 206 communities to two treated groups and one control group. In the first treated group, only local political leaders received detailed information about the gas discovery, the expected windfall, and the rights of the local population to it; In the second treated group, both local leaders and communities at large received the information; In the control group, no dissemination efforts were organized. The results showed that the exposure of communities to the discovery information increases local mobilization and decreases violence, whereas exposure of local leaders to the discovery information increases elite capture and rent-seeking. Bhattacharyya and Mamo (2021) set up another natural experiment to study the effect of natural resources (mineral resources and petroleum) on conflict in Africa in the period 1950-2008 at an even smaller level - the grid cell level with a resolution of $0.5^\circ \times 0.5^\circ$ latitude and longitude. They found that resource discovery reduces the likelihood of conflict onset within 10 years after resource discovery. A possible explanation is that the discovery improves local income measured by luminosity, thereby reducing the likelihood of conflict. However, Chisadza et al. (2024) found more intrastate conflicts within a year of a giant discovery, which is mainly driven by the effects on ethnic conflicts, while more interstate conflicts occurred only after five years, using a global panel of countries between 1970 and 2012 with giant oil and gas discoveries. By now, the effect of (discovery) on conflict is exceptionally bewildering, since there are insignificant (Cotet & Tsui, 2013a), positive (Chisadza et al., 2024; Lei & Michaels, 2014), and negative (Armand et al., 2020; Bhattacharyya & Mamo, 2021) results.

2. Different energy strategies in the post-Soviet space

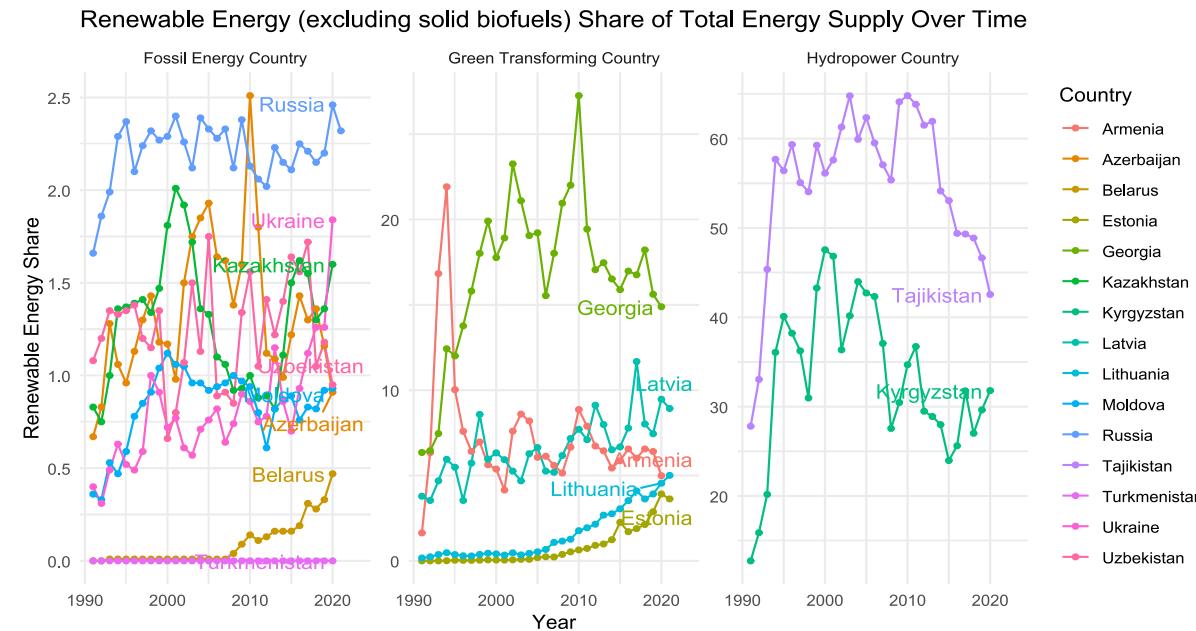
Post-Soviet countries share a similar historical background but have pursued drastically different energy strategies. Caspian economies rely much more on gas and oil, while Tajikistan and Kyrgyzstan make use of hydro energy extensively. Post-Soviet provides an ideal field to observe the influence of a giant discovery by minimizing the unobservable variables.

Furthermore, not so many studies examined the relationship between existing resources in post-Soviet countries and energy transformation.

The Soviet Union has long been a major energy producer. Still, its production rose spectacularly in the 1970s with the discovery and exploitation of huge Siberian oil and gas reserves, making it the world's largest energy producer. According to Western estimates, the USSR holds some 58 billion barrels of proven oil reserves, making up 6 percent of the world's reserves. The USSR has the largest natural gas reserves in the world, with 52 trillion cubic meters of proven and, constituting 40 percent of the world's total reserves. In 1989, its total energy production, including oil, natural gas, coal, hydroelectricity, and nuclear power, was nearly 1700 million tons of oil equivalent (MTOE). This was about 21 percent of global output, versus 20 percent for the United States, the world's second-largest producer. In terms of total energy production in 1989, gas accounted for 38% of domestic output, oil for 36%, coal for 20%, nuclear for 2.9%, and hydro for 3%. Renewable energy (excluding hydro power and wood) only accounts for about 0.1 percent (Kumar & Osband, 1991). The total electric power generation in the country reached 1,728 billion kWh in 1990. About 70% of installed capacity is from fossil-fueled power plants, about 12% is from nuclear power plants, and about 18% is from hydroelectric power plants (Rudenko, 1993). Therefore, all post-Soviet countries have almost no renewable energy industry, other than hydroelectric power plants in Russia, Ukraine, Georgia, Kazakhstan, Tajikistan, and Kyrgyzstan.

Despite the shared history, post-Soviet countries have pursued distinctly different energy paths. I categorize 15 post-Soviet countries into 3 groups: **Fossil energy countries**, if renewable energy excluding solid biofuels makes up for less than 2% of total energy supply; **Green transforming countries**, if renewable energy makes up for more than 2%; **Hydropower countries**, namely Tajikistan and Kyrgyzstan, where renewable energy from hydro accounts for almost a half of the total energy supply. TES comprises production + imports - exports - international marine bunkers - international aviation bunkers ± stock changes. Organizations like the International Energy Agency (IEA) consider solid biofuels a renewable energy source. Still, it can have environmental impacts (e.g., deforestation, particulate emissions) that make them less aligned with some renewable energy goals. The employment of solid biofuels also cannot reflect a country's investment and development in technologies like wind, solar, hydro, or cleaner, low-emission sources of energy. The Baltic countries and energy-sparse countries like Moldova, Belarus, and Ukraine have an increasing demand for solid biofuels. For fossil energy countries and Central Asian countries, the use of solid biofuels is specifically limited. To present a more nuanced and precise picture of renewable energy development since their independence (See Figure 2.1.), I excluded solid biofuels from renewable energy.

Figure 2.1. Renewable energy (excluding solid biofuels) share of total energy supply over time.



Note: Compiled by the author based on the IEA dataset.

2.1. Fossil energy country

Fossil energy countries are either oil and gas producing countries (Russia, Azerbaijan, Turkmenistan, Kazakhstan, Uzbekistan) or energy dependent countries (Ukraine, Moldova, Belarus). Oil and gas play a significant role in the economies of Russia, Azerbaijan, Kazakhstan, and Turkmenistan. According to the UNU-WIDER Government Revenue Dataset (GRD), more than half of Azerbaijan's government revenue is from resources for most of the years, in Turkmenistan around 50%, in Kazakhstan varying from 30% to 40%, and in Russia from 15% to 30%. The value of fuel exports is roughly equivalent to 20% - 30% of the GDP in Azerbaijan and Kazakhstan, and about 15% in Russia (calculated based on data from *Trade Map*, 2025; *World Development Indicators*, 2025). Mineral fuel export is the most exported product in these 4 countries, the share of fuel export in the value of total export accounts for 90% in Azerbaijan, 84% in Turkmenistan, 66% in Kazakhstan, and 58% in Russia, taking an average level from data in this century (*Trade Map*, 2025).

Facing green energy transformation, Russia attempts to establish itself as a guarantor of traditional energy and as a leading energy broker in the oil- and gas-rich countries of Eurasia. It seeks to exert influence and substantial leverage through assisting Eurasian petrostates to defend and maximize hydrocarbon exploration and sales rather than building a serious commitment to the development of renewable energy technologies. Russia has formed temporary alliances with Eurasian petrostates to forge common strategies in response to the shared energy transition crisis. On the other side, other than Kazakhstan, none of the fossil fuel producers are seriously developing renewables. As tackling climate change becomes an inseparable component of global consensus, “most Eurasian petrostates want to have it both ways: they mostly talk about big plans to expand their renewable portfolio while continuing to produce oil and gas” (Skalamera, 2022, p. 1649). Kazakhstan is the only exception among

petrostates, which has begun reshaping its energy landscape, making investments in clean energy to mitigate environmental risks. Kazakh President Kassym-Jomart Tokayev announced in 2022 that Kazakhstan will reach carbon neutrality by 2060 as part of the strengthened national climate plan (Satubaldina, 2020). In 2012, Kazakhstan, for the first time, had a 10 TJ renewable energy supply that was not from hydro and biomass. This number grows quickly to 15185 TJ in 2022. By the end of 2024, Kazakhstan had built a network of 148 renewable energy facilities, generating nearly 94600 TJ of clean power (Li, 2025).

Uzbekistan possesses 0.8 trillion cubic meters of gas, about 0.4% of the world's total reserve, but its production has already reached 1.1% of the world's total production. Its fuel export, experiencing a quick fall after the pandemic, only accounts for 4.6% of the total export value in 2023, ranking 5th in all commodities. This number in 2018, however, was 24.4%. Uzbekistan's gas was primarily exported to China and Russia. Since the Ukraine war, exports to Russia have been halted. New buyers like the United Arab Emirates, the USA, and Türkiye took over Russia's portion. Although gas exports have been shrinking due to shortages, they have not stopped (see Table 2.1.1.), because of the long-term contract for gas trade between Tashkent and Beijing. Since last year, officials have started compensating for the shortfall in domestic extraction by importing gas from Turkmenistan and Russia. In December 2022, for the first time, Uzbekistan concluded a direct - without the participation of a third party - short-term gas supply contract with Turkmenistan to import a total of 1.5 billion cubic meters in 3 months (2023a). In August 2023, Tashkent and Ashgabat signed a new contract to supply up to 2 billion cubic meters of Turkmen gas to Uzbekistan per year (KUN.UZ, 2023b). In October 2023, Uzbekistan began importing gas from Russia via Kazakhstan under a two-year deal signed with Russia's Gazprom, with about 2.8 billion cubic meters of gas per year. It is the first time that Uzbekistan, as a producer and exporter, is importing gas from Russia (Oziel, 2023). A recent World Bank report on achieving net-zero emissions in Europe and Central Asia noted that "Central Asia faces a tightening gas supply balance" and would likely be forced to make tough decisions to either form a "Central Asian Gas Union" with Russia or be forced to reduce exports to China (Putz, 2024).

Table 2.1.1. Gas export, import, and production in Uzbekistan from 2017 to 2023

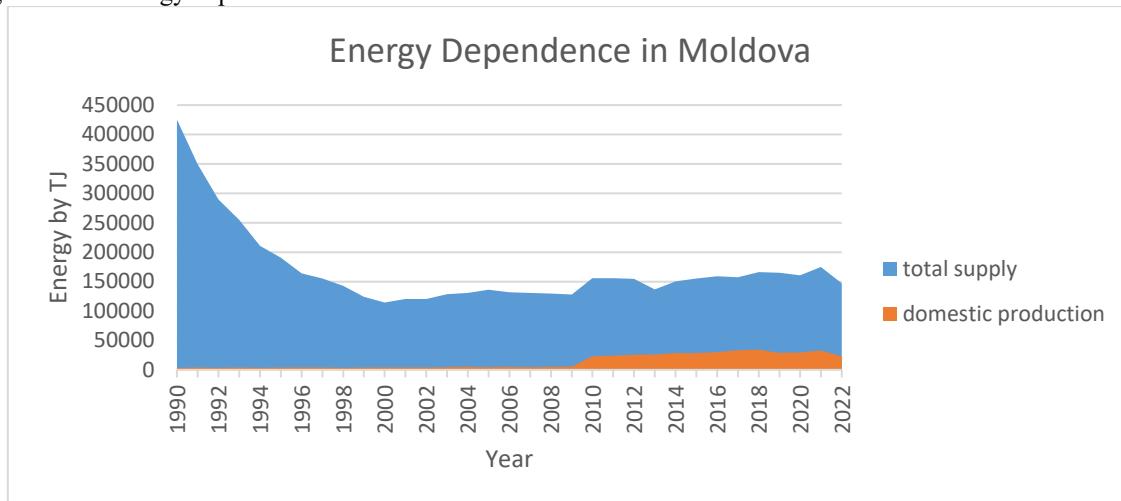
Uzbekistan	2017	2018	2019	2020	2021	2022	2023
Gas export value (Dollar thousand)	1,398,875	2,453,903	2,296,084	478,140	717,324	925,318	533,873
Gas import value (Dollar thousand)	45	118	213	50,408	154,471	281,862	696,640
Gas production (Billion cubic meters)	53.6	58.3	57.5	47.1	50.9	48.9	44.2

Note: Compiled by the author based on the Trade Map dataset and Statistical Review of World Energy.

Moldova's energy self-sufficiency is very low; with a mild but steady increase, domestic energy production only accounted for 4% of the total energy supply in 2009 (see Figure 2.1.1.). The most important domestic energy source is biofuels, making up two-thirds of the total production. In 2010, Moldova acceded to the Energy Community Treaty. For compliance with the Treaty and its related Annexes, Moldova needs to promote electricity produced from renewable energy

sources and the use of biofuels or other renewable fuels for transport (Energy Community, 2010). One of the most important projects is the Moldova Energy and Biomass Project, financed by the European Union and the United Nations Development Program (UNDP). It boosted the launch of a new industry in the Moldova, namely the production of bioenergy in rural areas (Energy and Biomass Project in Moldova, 2014). During 2011-2018, 265 schools, kindergartens, community facilities, and hospitals have installed biomass-fired heating systems (United Nations Moldova, 2018). Therefore, from 2010, Moldova can instantly increase the share of domestic energy production to 15%-20%, and **biofuels make up approximately 95% of the domestic production**. Besides, Moldova has a steady hydropower inflow, covering less than 1% of the energy supply. Since 2013, there have been a few installations of geothermal, solar, and wind energy. Moldova's mineral fuel import mainly relies on Romania (around 40%-60%) and Russia. Its imports from Russia fluctuated constantly, it dropped from 787 to 105 million dollars in 2023 compared to 2022.

Figure 2.1.1. Energy dependence in Moldova



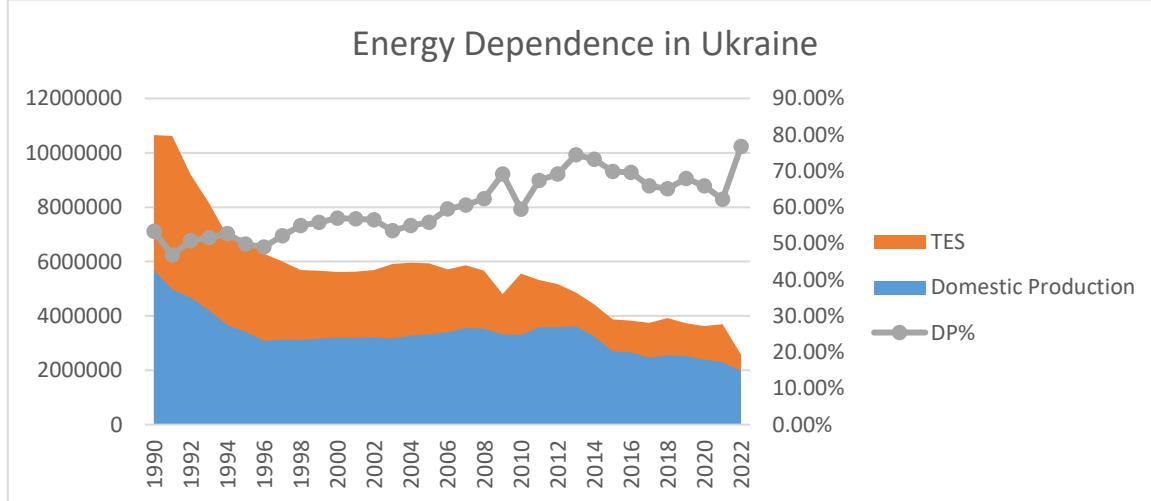
Note: Compiled by the author based on the IEA dataset.

Similar to Moldova, Belarus has a strong energy dependency on imported mineral fuels and a low domestic energy production with a growing focus on biofuels. Belarus has a continuous yearly output of mineral fuels around 100 000 TJ. Even though the share of domestic production in total energy supply increased from 7.61% in 1990 to 23.35% in 2022 due to the development of biofuels and the establishment of nuclear plants. The main emphasis in Belarus is on increasing the use of wood fuel, as it requires less capital investment than other types of renewable energy. Fuel from woody biomass (i.e. rough wood, pellets, chips and briquettes) is produced locally using modern harvesting and wood-chipping equipment (IEA, 2020a). The energy production from biofuels is around 80,000 TJ, 8 times the production 30 years ago. In November 2020, the first unit of Belarus's nuclear power plant at Ostrovets was connected to the grid, with the second unit connected in May 2023 (World Nuclear Association, 2024). The share of other forms of renewable energy was around 0.01% before 2011, then increased to less than 0.3% to date.

Under the Energy Capacity Development Strategy of the Republic of Belarus (2010), Belarus is determined to reduce its reliance on Russia as its single supplier of natural gas. However, Belarus's energy dependence is hardly reversed. More than 98% of fuels are still imported from Russia in regular years. Specifically, the country imports all its gas from Russia. In terms of nuclear energy, Russia lent up to \$10 billion for 25 years to finance 90% of the nuclear power plant. Russia's policy for building nuclear power plants in non-nuclear weapons states is to deliver on a turnkey basis, including the supply of all fuel and repatriation of used fuel for the life of the plant. The fuel is to be reprocessed in Russia, and the separated wastes will eventually be returned to the client country (World Nuclear Association, 2024). The dependence on Russian gas may be smaller, but in general, the function and maintenance of the nuclear plant still rely on Russia.

Ukraine has similar patterns to Belarus and Moldova, it heavily relies on non-renewable energy. Modern renewable energy accounts for about 1.5% of the total energy supply for a sustained period. In recent years, the consumption of biofuels and waste rose quickly to 6% of TES, due to the phasing out of natural gas price subsidies in the residential sector in 2015-16, which removed numerous distortions and made heat production from biomass fully competitive with heat produced from gas in both the individual and district heating sectors (IEA, 2020b). As shown in Figure 2.1.2., Ukraine is more energy-sufficient thanks to its resource reserves. But the Russian invasion exaggerates its dependence on fossil fuel coming from Russia and Belarus. After the Crimean War, Ukraine's import of fossil fuels dropped from about 80% to 50%; this trend continues to 2021, and now Ukraine imports no fossil products from these two countries. Its current priority is to disconnect from Russian energy networks. In March 2022, the electricity grids of Ukraine (and Moldova) were successfully synchronized with the Continental European Synchronous Area under emergency mode (Directorate-General for Energy, 2025b). According to the Energy Strategy of Ukraine (ESU) to 2035, only in the third implementation stage (2026-35) will Ukraine rapidly develop renewables and reduce greenhouse gas emissions (IEA, 2020b).

Figure 2.1.2. Energy dependence in Ukraine



Note: Compiled by the author based on the IEA dataset.

2.2. Green transforming country

Russia's war in Ukraine has also brought energy independence into focus for the Baltic region. The geopolitical tremors are fast-tracking the Baltic's energy transition, speeding up their pursuit of energy autonomy and the transition to a sustainable, low-carbon future. In terms of energy security, the Baltic states were isolated energy islands until 2014. The installation of the Klaipėda liquefied natural gas (LNG) terminal on Lithuania's Baltic coast changed it. It has enabled the formation of a natural gas market in Lithuania and opened opportunities for the country to import natural gas from all over the world. Hence, the Baltic States could largely cease importing Russian gas after Russia invaded Ukraine and instead import it from the US and Norway. Besides, to decrease the energy dependence on Russia, the Baltic States also enhanced interconnectivity among the Baltic States and Poland and shared the use of gas storage facilities in Inčukalns, Latvia (Beyer & Molnar, 2022). Furthermore, in 2023, Estonia, Latvia, Lithuania, and Poland signed a Political Declaration confirming their commitment to proceed at full speed to connect the electricity networks of the three Baltic States with continental Europe via Poland by February 2025. This is almost a year earlier than the previous deadline of the end of 2025 (Directorate-General for Energy, 2023a). On Feb 9, 2025, Estonia, Latvia, and Lithuania are fully independent from Russia's and Belarus's electricity systems and are integrated into the EU internal energy market (Directorate-General for Energy, 2025a).

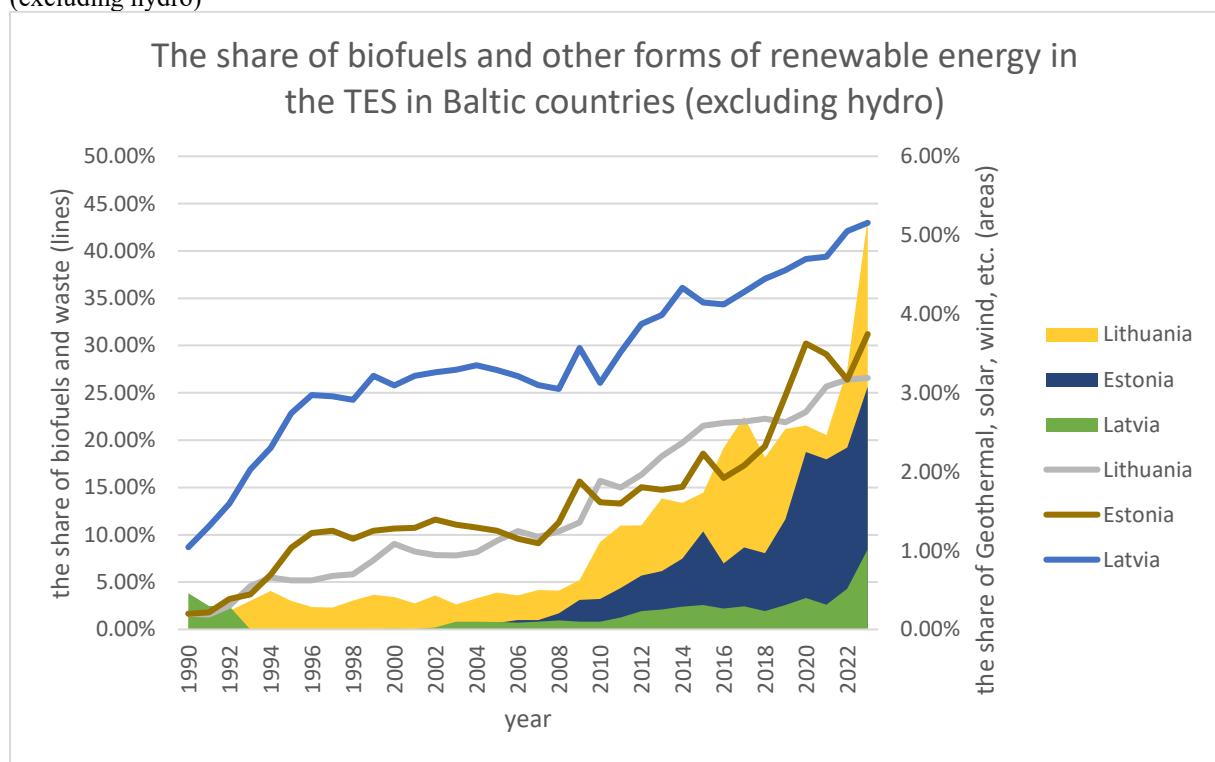
On the other hand, the revised Renewable Energy Directive EU/2023/2413 raises the EU's binding renewable target for 2030 to a minimum of 42.5% of total energy consumption, up from the previous 32% target, with the aspiration to reach 45% (Directorate-General for Energy, 2023b). By 2050, the EU strived to become an economy with net-zero greenhouse gas emissions. The 2050 long-term strategy, in line with the EU's commitment to global climate action under the Paris Agreement, is a legally binding target for the Baltic countries due to the European Climate Law. Both targets stimulate the Baltic countries further with green transformation. Lithuania's energy supply strongly depends on imports, as domestic production in recent years covered only about 30% of the total energy supply. Two-thirds of TES comes from oil and natural gas, and 32% from renewables (including biofuels and waste), in which only 5% is from geothermal, solar, wind, etc, in 2023. Bioenergy and waste cover about 80% of domestic energy production in recent years.

Estonia is unique among Baltic countries as its energy supply relies on oil shale (classified as coal), a hydrocarbon-rich sedimentary rock that has slightly higher energy density than lignite. Oil shale is mined domestically, burned to generate electricity and heat, and liquefied to produce shale oil, a synthetic crude oil (IEA, 2023b). Due to the development of renewable energies and biofuels, the share of coal in domestic energy production has dropped from 97% to 58%. Biofuels and waste cover about 40% of domestic energy production in recent years. Similar to Lithuania, two-thirds of TES in Estonia comes from fossil energy and one-third from renewables (including biofuels and waste), but only 3% if excluding biofuels and waste in 2023. Latvia's energy system is relatively more diversified, with sizeable shares of renewables in the form of hydro, which contributes to 5-7% of the energy supply yearly. The main source of energy supply in Latvia is fossil energy, accounting for 49% of the total energy supply in 2023,

with a shrinking scale. Bioenergy, drawn from domestic sources, covers more and more energy needs. In 2023, 43% of the total energy supply is from Biofuels and waste.

Over the past decade, the Baltic countries—Estonia, Latvia, and Lithuania—have not undertaken significant new large-scale hydroelectric projects. The primary hydroelectric facilities in Latvia and Lithuania were established in Soviet times, and recent years have not seen the commissioning of major new plants. Estonia has very limited hydroelectric capacity. In 2025, Estonia will begin the construction of its first pumped hydro energy storage plant in Paldiski with a capacity of 500MW, representing a significant milestone in developing the country's inaugural large-scale energy storage facility (Zero Terrain, 2024). Figure 2.2.1. shows how the Baltic countries developed all forms of renewable energies.

Figure 2.2.1. The share of biofuels and other forms of renewable energy in the TES in Baltic countries (excluding hydro)



Note: Compiled by the author based on the IEA dataset.

Armenia does not produce any fossil fuels; it has six known coalfields and some shale oil deposits, but the economic viability of mining these deposits has not been determined (IEA, 2023a). It has managed to cover about 30% of energy demand with domestic energy production for the last 20 years. This production comes mostly from nuclear (about 75%) and hydro (about 20%). Around 60% of TES comes from gas. All fossil fuels are imported, predominantly from Russia (73% in 2023) and Iran (14% in 2023). According to the Republic of Armenia Energy Sector Development Strategic Program to 2040 (2020), its energy policy priorities are maximizing the use of renewable energy, increasing energy efficiency, and extending the lifetime of the nuclear reactor. Besides, it aims to construct Armenia-Iran and Armenia-Georgia power transmission lines and infrastructures, which will play a decisive role in terms of having a power system of regional significance. In 2014, the government developed the Scaling-Up

Renewable Energy Program Investment Plan, which is an update of the Renewable Energy Roadmap developed in 2011 and includes comprehensive analyses of renewable energy potential, costs, and benefits, and the viability of specific technologies (IEA, 2023a). Since then, Armenia has started the development of renewable energy. In 2014, renewable energy from geothermal, solar, wind, etc., was only 14 TJ; in 2022, it has already grown to 2595 TJ, accounting for 5.74% of domestic energy production. Armenia aims to increase the share of solar power generation to at least 15% of domestic energy production or 6480TJ by 2030, outlined by the strategic program to 2040.

Georgia has had an increasing energy supply for 20 years. However, its domestic energy production remains limited, therefore, the share of domestic production drops from 53% in 2002 to only 22% in 2022. Hydropower is the most important domestic power source in Georgia. The generation volume increased 1.5 times to 38777 TJ, accounting for more than 70% of energy production. Biofuels and waste, the other main fuel source, account for 16% of domestic energy production. Gas is the most important energy source in Georgia, it mainly comes from Azerbaijan and Russia. After the Ukraine War, Georgia's imports from Russia increased. In 2023, of Georgia's imported fossil fuels, 46% is from Russia, 24% from Azerbaijan, and 9% from Romania. Georgia has determined this decade, between 2021 and 2030, to be the timeframe for the implementation of the country's Nationally Determined Contribution . It aims to reduce national GHG emissions unconditionally to 35% below the 1990 level by 2030 (Government of Georgia, 2018). According to the draft of the Integrated National Energy and Climate Plan of Georgia (NECP) (2023), Georgia will increase the share of renewable energy sources in final energy consumption to 27.4% by 2030.

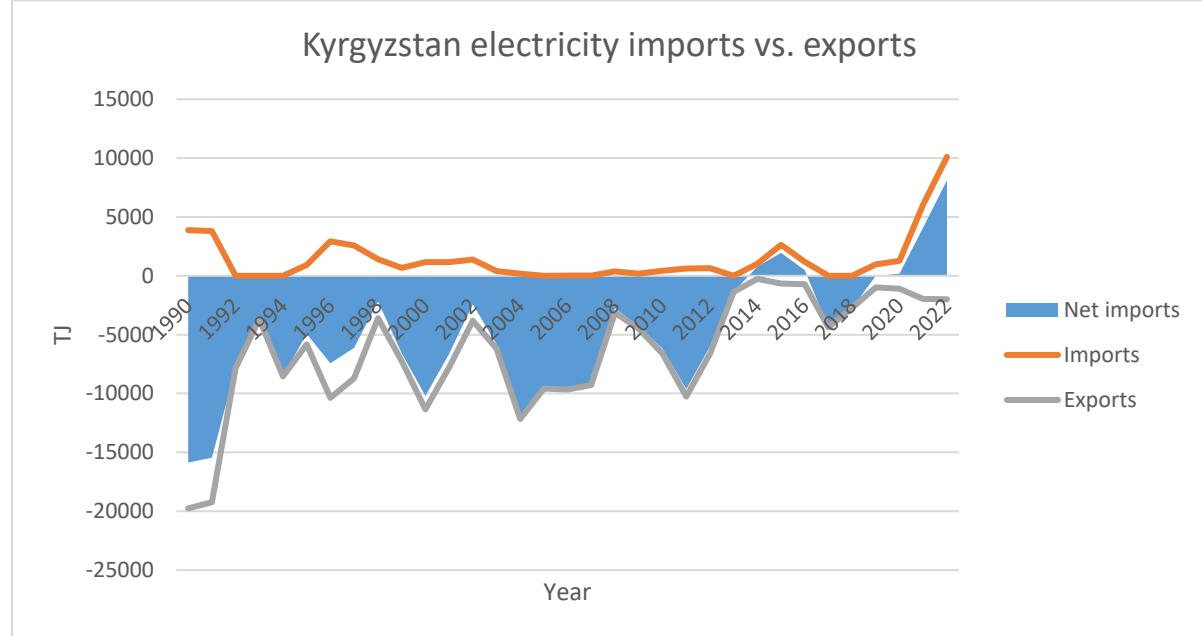
2.3. Hydropower country

Hydropower, as the largest clean electricity source, provides an essential foundation for the energy transition (IEA, 2023c). Hydroelectric power plants in Tajikistan and Kyrgyzstan are built on rivers that are tributaries of the two largest rivers of Central Asia - the Syr-Daria and Amu-Daria. Around 74% of the flow of the Amu Darya River is formed in Tajikistan, while 75% of the water resources of the Syr Darya basin are produced within Kyrgyzstan's borders. These two rivers cover the entire Central Asian region, and the economies of all Central Asian countries are highly dependent on the use of transboundary water resources. These characteristics impede further resilient development of hydropower in Tajikistan and Kyrgyzstan. Because of the seasonal nature of hydropower, electricity supplies in both countries are most reliable in spring and summer, when the demand of the domestic market can be fully met. However, in the autumn and winter, when the energy demand is the highest, Kyrgyzstan and Tajikistan face the problem of electricity shortages. Therefore, the energy policy of Tajikistan and Kyrgyzstan aims to alleviate the annual seasonal winter shortages and ensure uninterrupted access to energy for the population (Kosowska & Kosowski, 2022).

Tajikistan has been a net exporter of electrical energy already in Soviet times, it used Central Asia Power System (CAPS) to export surplus processed electricity in summer and import energy in winter. In 2009, Uzbekistan blocked Tajikistan's participation in CAPS owing to conflict over the region's water resources. Before 2009, Tajikistan's electricity import amounted to 17000 TJ with fluctuation; after 2009, it fell under 1000 TJ. In 2018, energy cooperation

between the countries was renewed, and Tajikistan's electricity import and export received robust growth. In summer, the surplus of electrical energy could reach 3-7 billion kWh. At present, the government is planning to diversify energy sources (including the introduction of non-hydro renewables), modernize the existing energy infrastructure, improve energy saving, and increase regional integration. Similarly, Kyrgyzstan sent the overflow of electricity for export to Russia, China, Kazakhstan, Uzbekistan, and Tajikistan. Total annual exports were 2-2.5 kWh. However, with growing domestic consumption and losses resulting from an antiquated electricity grid, the country transformed from a net exporter to a net importer of electrical power in 2014-2016 and from 2019 onwards (see Figure 2.3.1.). Both Central Asian countries are actively supporting CASA-1000, a project to build an electricity transmission line from Kyrgyzstan and Tajikistan to Afghanistan and Pakistan to export surplus electricity during the summer season. CASA-1000 is intended to provide Tajikistan and Kyrgyzstan with a steady source of income that can be used to alleviate severe winter energy shortages and improve the level of economic security of both countries (Kosowska & Kosowski, 2022).

Figure 2.3.1. Kyrgyzstan electricity imports vs. exports



Note: Compiled by the author based on the IEA dataset.

But it is fossil fuels, namely oil and coal, that fill the growing energy gap in Tajikistan and Kyrgyzstan. In 2022, 58% of TES in Tajikistan came from fossil energy, and 76% of TES in Kyrgyzstan came from fossil energy, which is still on an upward trend. Both countries are among the lower-middle-income countries and currently barely have any renewable energy industry other than hydropower. According to the National Development Strategy of the Republic of Tajikistan for the Period up to 2030 (2023), electric power system capacity should be diversified at least by 10% through increased use of coal, oil, gas, and renewable energy sources other than hydro. Strategy 2030 also points out the need to create conditions for the development of renewable energy and to reduce the share of imported energy resources through the development of renewable energy. The National Development Strategy of the Kyrgyz

Republic for 2018-2040 (2018) set a target of the share of renewables to be at least 10% of the country's total energy balance. However, there is either an economic and technical analysis of how to achieve the stated 10% or a clear implementation plan.

Worth mentioning, 11 post-Soviet countries (except for Russia and the Baltic countries) are the focus countries of the EU4Energy program, implemented by the IEA and the European Union along with the Energy Community Secretariat and the Energy Charter Secretariat. The program is designed to support its 11 focus countries in implementing sustainable energy policies and foster cooperation on energy sector development. EU4Energy builds on the success of the long-running INOGATE Program (formerly Interstate Oil and Gas Transportation to Europe), its second phase (2021-2025) focuses solely on the six countries of the EU's Eastern Partnership (IEA, 2025).

3. Theoretical framework and methodology

This chapter introduces the theoretical framework, complementing the theory review in the previous chapter and the methodology. First, the resource curse, the path dependence in the energy sector termed as carbon lock-in, and the green paradox are briefly presented. Subsequently are the hypotheses based on the theories. Second, the justification for the natural experiment method is provided, forming the foundation of this study.

3.1 Theories and hypotheses

Despite my extensive literature review, I did not find any research on the impact of giant resource discoveries on green transformation. The short-term effect of a resource shock is unknown. However, the role of governance as a moderator in determining the effect of resource discovery has been confirmed by both empirical evidence and a large number of case studies. Brazil's fiscal responsibility law and credit constraints likely have helped municipals avoid fiscal excesses following discovery announcements (Katovich, 2024). Botswana escaped the resource curse because it installed a predictable system of regulation of its diamond wealth, insisted on anticorruption policies promoting transparency and accountability in the public sector, and established a system of governance/institutions that encourages growth and discourages rent-seeking (Orre & Rønning, 2017). Following the tradition of resource curse literature, many papers on resource discoveries have also considered the moderating role of institutions in quantitative analysis (to name a few: Alsharif & Bhattacharyya, 2019; Bhattacharyya et al., 2017; Masi & Ricciuti, 2019; Okada & Samreth, 2021; Smith, 2015). No matter the news shock of a giant oil and gas discovery will drive the country towards or away from renewable energy, the quality of institutions should presumably moderate this process - a better institution will facilitate green transformation after a giant discovery. Here are the hypotheses for the short-term effect of giant discoveries:

H_s: In countries with better institutions, giant discoveries will lead to fewer setbacks in green transformation compared to countries with weaker institutions.

Available theories provide the framework to analyze the long-term effects of giant resource discoveries on green transformation. In the long term, the impact of giant resource discoveries

is the impact of resources. It is straightforward that energy resource discovery will hinder green transformation. A popular theory that scholars turn to is “path dependence”. Path-dependent processes form and develop inertial resistance to large-scale systematic shifts driven by favorable initial social and economic conditions. Due to path dependence, many technical, institutional, and behavioral systems with known technical and environmental disadvantages are entrenched. When these disadvantages include carbon emissions to the atmosphere, the path dependence is termed carbon lock-in. A giant discovery can trigger and reinforce two kinds of carbon lock-in: infrastructural and technological lock-in, and institutional lock-in. Infrastructures like pipelines, refineries, and refueling stations will be installed after a giant discovery. New infrastructure investments deepen ties between the state and fossil fuel sectors, and increase fiscal dependence on resource rents. The institutional lock-in can be regarded as the formation and development of an interest group. The restricted horizons and status quo biases of politicians make it difficult to overturn governmental policies. Hence, existing institutions can strengthen the interests of oil and energy companies, which wield the most influence over their creation and modification. Therefore, the networks that arise among policymakers, institutional bureaucracies, and powerful energy interests further reinforce and stabilize carbon-intensive systems. A giant resource discovery starts the loop: “those actors that most benefit from existing energy infrastructures push for institutional rules that further their interests, provide them with greater resources, reinforce their political and economic dominance, and allow them to deploy yet greater resources to shape institutions to their benefit” (Seto et al., 2016, p. 434). Accordingly, giant discoveries can cause an increase in TES, FE supply, nonrenewable energy share, a decrease in RE (excluding biofuels), energy efficiency, and the investment in renewable energy.

The green paradox introduced by Hans-Werner Sinn (2015) provides another explanation. Traditional green policies focus on reducing demand for fossil fuels through taxes, subsidies for renewables, and raising public awareness of climate change. However, “while most of us perceived these developments as a breakthrough in the battle against global warming, resource owners viewed them as efforts that threatened to destroy their markets. Thus, in anticipation of the implementation of these policies, they accelerated their extraction of fossil fuels” (p. 240). In the spirit of Hotelling (1931), resource owners will choose portfolios that equalize the rates of return between keeping resources underground and selling them. Under the Hotelling rule, resource owners must base their behavior on expectations of future prices. This means that policies aimed at limiting or reducing the possibility of generating resource-derived revenues in the future will induce resource owners to bring their sales forward to the present. Therefore, green policies aimed at reducing future fossil fuel demand will incentivize resource owners to extract and sell their fossil fuel reserves sooner rather than later to maximize their profits, in anticipation of a diminishing market and a lower interest in the future. Instead of slowing down climate change, green policies accelerate it. Apparently, all four fossil energy countries in the post-Soviet space are not bothered by so-called green policies, as they are not aimed at promoting renewables. There are no active plans to fade out traditional energy in Russia, Azerbaijan, Kazakhstan, and Turkmenistan. But most gas and oil extracted there are redirected to industrial countries. Mineral fuel export is the most exported product in these four countries,

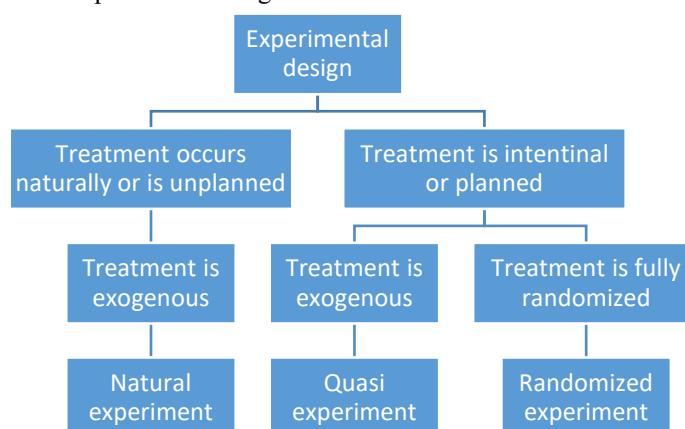
the share of fuel export in the value of total export accounts for 90% in Azerbaijan, 84% in Turkmenistan, 66% in Kazakhstan, and 58% in Russia, taking an average level from data in this century (*Trade Map*, 2025). Facing future green policies, giant oil and gas discoveries that increase energy reserves, will stimulate the extraction to maximize their interest. Only export-oriented resources would be influenced by the “backfire” of green policies. But in the long run, it will bind the state with the resource economy even further, increasing resistance to transformation. Here are the hypotheses for the long-term effect of giant discoveries:

H_L: Countries with previous resource discoveries will experience a worsening in green transformation in the long term, compared to countries without recent resource discoveries.

3.2 Natural experiment

A natural experiment occurs when a particular treatment has been implemented naturally or unplanned (Leatherdale, 2019). Natural experiment studies combine features of experiments and non-experiments. A natural experiment differs from a true randomized experiment because the latter has randomized controlled trials, in which treatment is allocated randomly by researchers. Still, the exogeneity of treatments in a natural experiment provides a framework for causal analysis, fundamentally differing from observational designs (de Vocht et al., 2021). A natural experiment is close to non-randomized experimental research designs, more commonly known in the social sciences as quasi-experimental designs. In a natural experiment, the treatment is introduced beyond the will of researchers and lacks a policy motivation, while in a quasi-experiment, the program or treatment is consciously implemented to produce some changes in the world (see Figure 3.2.1.). Therefore, the terms natural and quasi-experiment are mostly interchangeable, both referring to any study that falls short of a true randomized experiment treatment (Remler & Van Ryzin, 2021).

Figure 3.2.1. Classifications of experimental designs



Note: Adapted from Remler and Van Ryzin (2021).

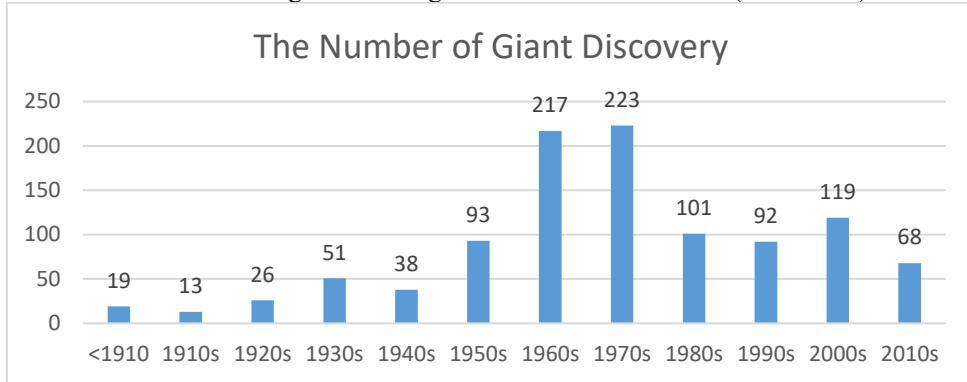
A normal discovery (i.e., subgiant) is apparently not exogenous because many factors affect and determine it, such as gas and oil prices, investment, technology, and policy environment. In fact, “discoveries of smaller fields are more within a predicted set of outcomes” (Cust & Mensah, 2020, p. 16). In the widest sense, population and the discovery of oil and gas have a

positive correlation. Countries with larger populations tend to have softer soil, under which oil is more likely to be found (Smith, 2015). Among resource-poor countries, a higher population in 1950 leads to higher possibilities of discovery after 1950; this result remains the same even if controlling for land area. In contrast to normal-sized discoveries, a giant discovery is considered unpredictable.

First, the political, social, and economic situation prior to the giant discovery can hardly be correlated to a giant discovery. Lei and Michaels (2014) have found no empirical evidence of significant economic or political changes in the last five years before a giant discovery leading to it; temporary lulls prior to conflicts do not lead to discoveries either. Pre-existing economic and political variables do not predict the date of a giant discovery (Alsharif & Bhattacharyya, 2019, 2024; Bhattacharyya et al., 2017; Bhattacharyya & Keller, 2021; Harding et al., 2020; Sobrinho & Ruzzante, 2022). Tested factors (mostly lagged) include GDP growth per capita, international commodity price, international oil price, investment (% of GDP), expenditure (% of GDP), government debt (% of GDP), CPI inflation, Polity score, Governance indicator, population, human capital, etc. **Second, drilling does not promise a discovery.** The exploration intensity proxied by wildcat drilling is not correlated with a giant discovery in a given country-year (Bhattacharyya et al., 2017; Bhattacharyya & Keller, 2021). More directly, the probability of a giant discovery conditional on exploration drilling wells is only around 2%. “There is no deterministic relationship between exploration and discovery. Exploring for 100 years does not guarantee a giant discovery” (Toews & Vézina, 2022, p. 1049). For example, the first offshore well in South African waters discovered the gas field in 1968. Since then, at least 300 offshore oil and gas wells have been sunk. But only until 2019, French oil company Total made the first giant oil and gas discovery off South Africa’s coast (Roux et al., 2004). One might argue that the announcement of the precise timing of discovery could be manipulated by politicians and the government for political purposes. The Giant oil and gas field discoveries 1868-2018 dataset is to some degree immune to such possibilities as the reported discovery dates are from “public datasets, oil and gas company websites, press release news, news articles, industry magazines, specialized blogs and research papers” (see codebook, Cust et al., 2021, p. 2). It received an independent verification. Therefore, a rare, unpredictable giant discovery is likely to be exogenous and can be seen as the treatment in a natural experiment.

However, in theory as well as in reality, the giant discovery of oil and gas is not randomly distributed on the globe, either chronologically or geographically (see Figures 3.2.2. and 3.2.3.). It is constrained by human extraction history, technology, as well as the uneven distribution of resources. With the outbreak of World War I, the global oil demand surged, and it stimulated exploration efforts. Furthermore, new technologies such as the seismograph, aerial surface plotting, and micropaleontology significantly improved exploration efficiency in the 1920s and 1930s. Following World War Two, ever-increasing military demand from imperial armed forces and the expanded use of automobiles drove the demand for gas and oil and, therefore, exploration further (Alsharif & Bhattacharyya, 2019).

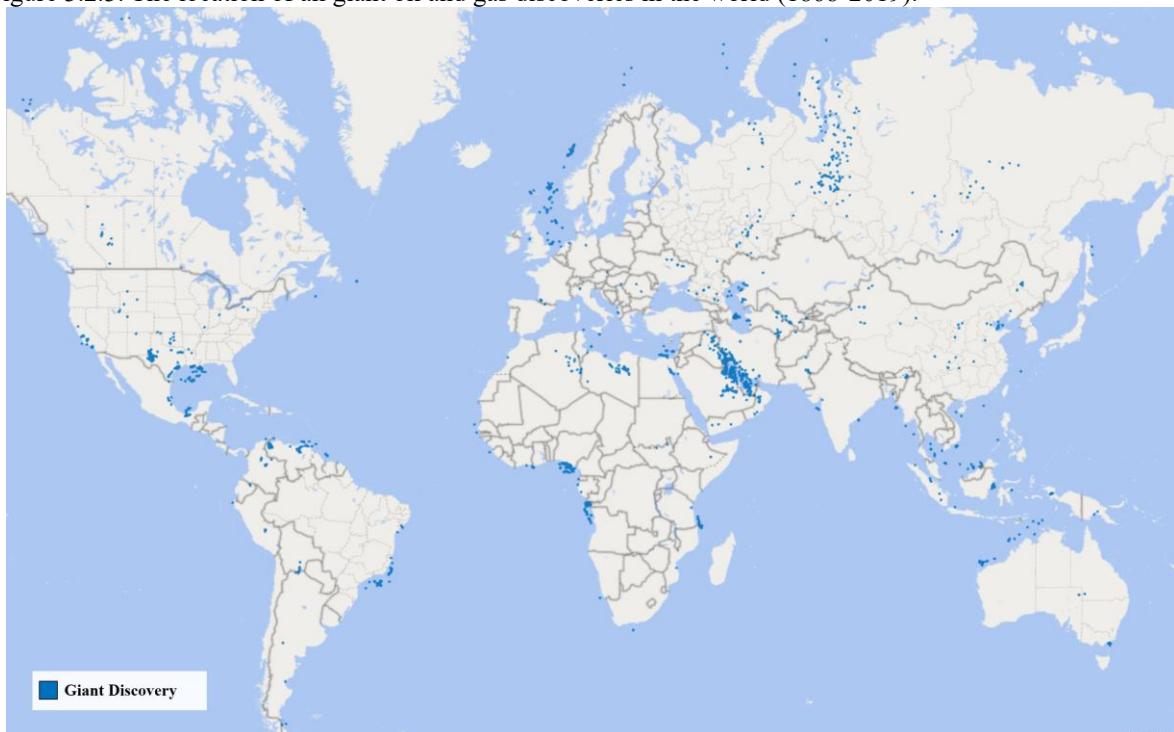
Figure 3.2.2. The time distribution of giant oil and gas discoveries in the world (1868-2019)



Note: Compiled by the author based on the Giant oil and gas field discoveries 2018 dataset.

In order to obtain reliable estimates, I approximate my natural experiments to a randomized control trial in two means. First of all, I control for the only identified confounder – **previous discoveries**. When Lei and Michaels (2014) exploited the possibilities of a giant resource discovery as pioneers, they found that giant oilfield discoveries in a country’s recent past increase the odds that it finds a giant oilfield in the recent. This serial correlation results from different reasons. Looking at the distribution of giant discoveries on the globe (see Figure 3.2.3.), most discoveries are concentrated in the Persian Gulf, the North Sea, West Siberia, the Caspian Basin, and so on. Because oilfields are close to each other, one finding may lead to another. Besides, this correlation could be driven by a fundamental feature of the extractive industry, “learning-by-doing”: past discoveries enhance geologic and technical knowledge as well as the efficiency of drilling activity, which in turn makes future discoveries more likely to occur (Sobrinho & Ruzzante, 2022).

Figure 3.2.3. The location of all giant oil and gas discoveries in the world (1868-2019).



Note: Made by the author based on the Giant oil and gas field discoveries 2018 dataset.

I also control for **country-fixed effects and time-fixed effects** to imitate a randomized control trial. Although discoveries (treatments) were not randomly assigned to country-years (treatment groups) as in a randomized controlled trial, I argue that the distribution of potential confounding variables across treatment groups appears to be similar to what one would expect in a randomized experiment, if country and time-fixed effects are controlled. In short, as-if randomization stands when controlling for both country- and time-fixed effects. Country-fixed effects capture unobserved time-invariant characteristics such as geographical location and the uneven distribution of resource endowment. Time-fixed effects control for common shocks, such as post-Soviet countries' transition, global business cycles, and international crude oil and gas price changes.

4. Empirical strategy and data

I use a panel dataset covering all 15 post-Soviet countries observed over the period from 1991 to 2022-2024. To examine the effect of giant oil discovery on green transformation, I estimate the following model (1), in spirit to Lei and Michaels (2014):

$$Y_{t+i} = \beta_1 X_t + \beta_2 X_t I_t + \beta_3 I_t + \beta_4 P + C + T + \varepsilon_t \quad (1)$$

Y_{t+i} is the dependent variable indicating the degree of green transformation in the year of $t + i$. It includes four aspects of green transformation: energy consumption, energy mix, energy efficiency, and investment in renewable energy. t is the year of discovery; i starts from the year of the discovery ($i = 0, 1, 2, \dots, 9$). X_t is the dummy of giant discovery in the year of t in a country; 0 indicates no giant discovery. I_t depicts the quality of the institution in the year of t . Using the institutional quality in the year of discovery excludes the influence of giant discoveries on institutions. $X_t I_t$ determines how the quality of the institution influences the strength and direction of the relationship between X and Y . P controls for any previous giant discoveries in the past 10 years in the country (from $t - 1$ to $t - 10$), it is a dummy variable with 0 meaning no previous findings. C and T control for country fixed effects and time fixed effects. ε_t is the error term. The coefficient of main interest is $\beta_1, \beta_2, \beta_4$. β_1 depicts the causal relationship between giant discovery and green transformation outcomes, if any. β_2 depicts how the institutional quality will influence green transformation outcomes, given a giant discovery. β_4 depicts the differences between countries with discoveries and countries without.

4.1. Independent variable: giant discovery

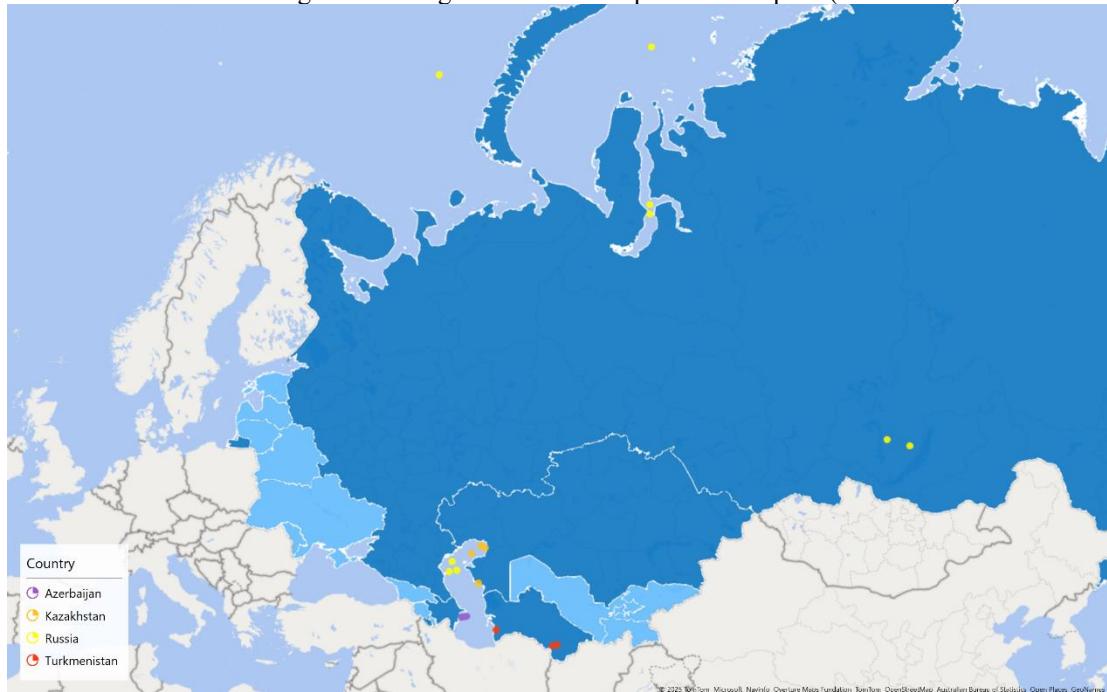
Table 4.1.1. Giant resource discovery in post-Soviet countries from 1991 to 2019

Country	Year	Location	Type	Size	EUR_MMBOE	NPV (Million)
Azerbaijan	1999	Offshore	Gas	Giant	4483.333	309.14749
Azerbaijan	2010	Offshore	Gas	Giant	700	216.33098
Kazakhstan	2000	Offshore	Oil	Supergiant	13333.333	50587.09
Kazakhstan	2001	Onshore	Gas	Giant	716.667	139.15199
Kazakhstan	2002	Offshore	Oil	Giant	508.333	3865.5649
Kazakhstan	2003	Offshore	Oil	Giant	700	5803.7715
Russia	1991	Offshore	Gas	Giant	530.093	62.74004
Russia	2000	Offshore	Gas	Giant	1060.163	193.19142
Russia	2000	Offshore	Gas	Giant	2833.333	409.40067
Russia	2002	Offshore	Gas	Giant	809.957	122.6316
Russia	2004	Onshore	Gas	Giant	916.667	214.80968
Russia	2005	Offshore	Oil	Giant	700.09	10723.639
Russia	2007	Onshore	Gas	Supergiant	7000	1505.3534
Russia	2008	Offshore	Oil	Giant	730	20107.785
Russia	2014	Offshore	Oil	Giant	4000	73215.969
Turkmenistan	1995	Onshore	Gas	Giant	1029.117	102.98496
Turkmenistan	2006	Onshore	Gas	Supergiant	22333.333	3293.8328
Turkmenistan	2010	Onshore	Gas	Giant	500	164.81459

Note: Compiled by the author based on the Giant oil and gas field discoveries 2018 dataset.

Giant oil and gas field discoveries 2018 dataset (2021) updates and extends the dataset on giant discoveries previously published by Horn in 2014. The new dataset contains giant fields that were discovered between 1868 and 2019; **giant oil and gas field discoveries are defined as those with estimated ultimate recovery (EUR) reserves greater or equal to 500 million barrels of oil equivalent (MMBOE)**, and supergiant discovery EUR is more than 5000 MMBOE. The net present value (NPV) is in nominal million US dollars, it's a multiple of the EUR and oil or gas price with a certain discount rate. As shown in Table 4.1.1., there are 18 giant discoveries, including 3 supergiant discoveries in Azerbaijan, Kazakhstan, Russia, and Turkmenistan. Valid country-year observations are 17 since Russia had 2 discoveries in 2000. Even though most giant discoveries are in the Caspian region (see Figure 4.1.1.), the range of discovery is fairly encompassing in terms of country location, covering Eastern Europe, the South Caucasus, and Central Asia. 6 out of 18 giant discoveries are onshore, and 12 are offshore. In the 1950s-1980s, Uzbekistan also had 11 giant gas discoveries. There were a few in Ukraine and Tajikistan in the 1950s-1960s, too. However, these discoveries will not be accounted for in the scope of this research.

Figure 4.1.1. The location of all giant oil and gas discoveries in post-Soviet space (1991-2019)



Note: Made by the author based on the Giant oil and gas field discoveries 2018 dataset.

4.2. Control variable: the quality of the institution

Many datasets provide information on the quality of institutions (see Table 4.2.1.). The *Worldwide Governance Indicators* (2024), *Comprehensive State Capacity Index* (2022), *State Fragility Index and Matrix, 1995-2018* (2018), and *Global State of Democracy Indices* (GSOD, 2024) provide comprehensive scores on the overall quality of state institutions. I aggregated all six indicators of WGI into a single index for governance, ranging from -15 to 15. Higher value corresponds to better governance. O'Reilly state capacity index constructs a comprehensive state capacity index, using principal components of six indicators from the V-Dem dataset. Not like historic state capacity measurements that capture only one element of state capacity, namely fiscal capacity, the comprehensive state capacity index reflects the overall quality of a state's institutions. The State Fragility Index and Matrix 2018 scores countries on both effectiveness and legitimacy in four performance dimensions: security, political, economic, and social. It combines scores on the eight indicators and ranges from 0 “no fragility” to 25 “extreme fragility”. For clarification, I flipped the scale so that higher values always reflect better institutional quality (25 means “no fragility” while 0 means “extreme fragility”). A country's fragility is closely associated with its state capacity to manage conflict, make and implement public policy, and deliver essential services, and its systemic resilience in maintaining system coherence, cohesion, and quality of life, responding effectively to challenges and crises, and sustaining progressive development. In the GSOD indices, the rule of law is regarded as one of the four attributes of democracy. Meanwhile, it captures the overall quality of institutions by composing judicial independence, absence of corruption, predictable enforcement, personal integrity, and security. It is scaled to range from 0 to 1.

Specifically, an amount of indicators measures the quality of political institutions in more detail. WGI reports some of the most important individual governance indicators: government

effectiveness, regulatory quality, and the rule of law. In the Varieties of Democracy Dataset v15, the rule of law index (v2x_rule) is formed by taking the point estimates from a Bayesian factor analysis model of 15 indicators from V-Dem. It reflects “to what extent are laws transparently, independently, predictably, impartially, and equally enforced, and to what extent do the actions of government officials comply with the law” (see codebook, *V-Dem Dataset v15*, 2025, p. 308). The sub-attribute of GSoD, predictable enforcement (scaled to range from 0 to 1), denotes “the extent to which the executive and public officials enforce laws in a predictable manner” (see codebook, *The Global State of Democracy Indices, 1975-2023*, 2024, p. 154). The component variable executive constraints (XCONST) of the Polity5 Project “refers to the extent of institutionalized constraints on the decision-making powers of chief executives, whether individuals or collectivities” (see codebook, *Polity5 Project, Political Regime Characteristics and Transitions, 1800-2018*, 2018). These constraints may be imposed by any “accountability groups”; it could be legislatures in Western democracies, the ruling party itself in a one-party state, councils of nobles or powerful advisors in monarchies, the military in coup-prone polities, or a strong, independent judiciary as in many states. This indicator evaluates the quality of institutions, not depending on regime type, avoiding regime bias. A seven-category scale is used, with 1 indicating executive owning unlimited authority, and 7 indicating executive parity or subordination.

Past researches seldom consider the possibility of economic institutions as moderators. Economic institutions may have close ties with traditional institution quality score, and also correlate with corruption, but they still depict some aspects missing in the political institution. Economic institution reflects the freedom, globalization, and independence of economic activities. Compared to traditional political institutions, economic institutions could be regarded as exogenous, as economic institutions are not subject to the risk of deterioration caused by resource discovery. The overall effects of discovery on economic institutions are not present statistically, indicating that good economic institutions may be a more robust safeguard against the natural resource curse. Political institutions can mitigate aspects of the resource curse, but they can also be eroded. “Effective market institutions allocate abundant resource rent productively, while in some circumstances, political institutions are influenced by the very resources that they are designed to allocate” (O'Reilly & Murphy, 2017).

The Index of Economic Freedom (IEF), published by the Heritage Foundation, measures economic freedom based on 12 quantitative and qualitative factors grouped into four broad categories of economic freedom: rule of law, government size, regulatory efficiency, and open markets. Each indicator within these categories is graded on a scale of 0 to 100. A country's overall score for economic freedom is the arithmetic mean of all 12 indicators. Fraser Institute's Economic Freedom of the World (EFW) publishes the Economic Freedom Summary Index, which measures the degree to which the policies and institutions of countries permit people to make their own economic choices from 2000 to 2022. However, data for Turkmenistan and Uzbekistan are missing.

Central Bank Independence - Extended index (CBIE, 2025) is an index of de jure central bank independence, it is computed as the average of the scores across the six dimensions of the index: Governor and central bank board, monetary policy and conflict resolution, objectives,

limitations on lending to the government, financial independence, and reporting and disclosure. The index ranges from 0 to 1, where 0 corresponds to the lowest level of independence and 1 to the highest level. However, data for Armenia and Tajikistan are missing. The KOF Globalisation Index measures de facto and de jure globalization from economic, social, and political dimensions. Specifically, economic globalization reports trade and financial globalization. The index is normalized to a scale from one to one hundred, where 100 is assigned to the maximum value over the whole sample of countries and the entire period.

Table 4.2.1. Indicators for the quality of institutions.

Moderator	Indicator name	Indicator ID	Dataset	Time range	Count
Overall Institution	Worldwide Governance	WGI	The Worldwide Governance Indicators	1996 - 2022	361
	State Fragility Index	SFI	State Fragility Index and Matrix	1995 - 2018	360
	Comprehensive State Capacity Index	CSCI	O'Reilly & Murphy Comprehensive State Capacity Index	1991 - 2023	481
	Rule of Law	GSD_rl	Global State of Democracy	1991 - 2023	495
Political Institution	Executive Constraints	PLTV_xconst	Polity V Annual Time-Series, 1800-2019	1947 - 2018	452
	Government Effectiveness, Estimate	WGI_ge	The Worldwide Governance Indicators	1996 - 2022	360
	Rule of Law, Estimate	WGI_rl	The Worldwide Governance Indicators	1996 - 2022	360
	Regulatory Quality	WGI_rq	The Worldwide Governance Indicators	1996 - 2022	360
	Rule of Law Index	VD_rl	Varieties of Democracy Dataset version 13	1991 - 2023	495
	Predictable Enforcement	GSD_rl_pe	Global State of Democracy	1991 - 2023	498
Economic Institution	Economic Freedom Summary Index	EFW	Economic Freedom of the World Index by Fraser Institute	2000 - 2022	311
	Index of Economic Freedom	IEF	Index of Economic Freedom by the Heritage Foundation.	1996 - 2025	414
	Central Bank Independence - Extended Index	CBIE	Central Bank Independence - Extended Index	1990s-2023	397
	Economic Globalization Index	EcGI	KOF Index of Globalization: Economic Globalization.	1991 - 2022	480

Note: Compiled by the author.

4.3. Dependent variables

The International Energy Agency (IEA) provides data on total energy supply (TES), energy mix, and energy efficiency. TES is expressed in millions of tonnes of oil equivalent and as an index with values in the year 2000 normalised to equal 100 (TES_index). Fossil energy (FE) supply includes coal, natural gas and oil in PJ. Renewable energy supply (RE) in PJ includes hydro, geothermal, solar (thermal and PV), wind, and tide/wave/ocean energy, as well as combustible renewables (solid biomass, liquid biomass, and biogas) and waste (renewable municipal waste). Renewable energy supply excluding solid biofuels (RE_exbio) in PJ excludes solid biomass, that is, primary solid biofuels and charcoal, to avoid distortions due to the traditional use of biomass for cooking and potential environmental risks associated with its unsustainable sourcing. I calculated fossil energy per capita, renewable energy per capita and renewable energy excluding biofuels per capita (GJ per capita); population data is extracted from World Bank. There are two different ways to measure the renewable share of energy: one is SDG_7.2.1, which records the share of renewable energy in total final energy consumption (TFC); the other records the share of renewable energy in TES. Energy intensity SDG_7.3.1 is calculated as TES/GDP (MJ per 2017 USD PPP), depicting the amount of TES needed for one unit of GDP change. For consistency, I transform energy intensity into energy efficiency (GDP/TES, 2017

USD PPP per GJ), showing how much economic output is produced per unit of energy used; the higher the index, the more efficient it is. I use GDP at purchasing power parity (PPP) because it adjusts for price level differences, ensuring that comparisons across countries over time are more straightforward. Here, SDG 7 refers to one of the Sustainable Development Goals (SDGs): affordable and clean energy, which aims to ensure access to affordable, reliable, sustainable, and modern energy for all.

IRENA publishes detailed statistics on investment in the energy sector (2021 USD million) and SDG 7.a.1. Investment in the energy sector is the financial flow in the form of commitments originating from public institutions like governments, multilateral development banks, and other public finance institutions. These flows include as much information as possible, but they are not exhaustive of all the global flows from public institutions. SDG indicator 7.a.1 reports international financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems. SDG 7.a.1 follows the same methodology as investment in the energy sector. Unlike the public flows, the SDG 7.a.1 international public flows exclude flows inside one country, flows directed to non-renewable technologies, flows to developed countries, and flows directed to multinational recipients not elsewhere specified. These data are collected directly from members using the IRENA Renewable Energy Statistics questionnaire and supplemented by desk research where official statistics are unavailable. An overview of dependent variables is presented in Table 4.3.1.:

Table 4.3.1. Indicators measuring the green transformation

Green transformation		Indicators
Energy supply		TES
		TES Index
		TES/cap
Energy mix	Quantity	Fossil energy
		RE
		RE_exbio
	Quantity per capita	Fossil energy/cap
		RE/cap
		RE_exbio/cap
	Proportion	RE/TFC (SDG_7.2.1)
		RE/TES
		RE_exbio/TES
Energy efficiency		GDP (PPP)/TES (1/SDG_7.3.1)
Investment	Quantity	SDG_7.a.1
	Proportion	RE_inve/investment

Note: Made by the author.

5. Results

5.1 Energy supply

A giant discovery is associated with a decrease in total energy supply (TES) in the first few years following the event. This negative correlation is particularly strong in models that include World Governance Indicators (WGI) (see Table 5.1.1.). In contrast, previous discoveries are found to have a stable and positive long-term effect on TES, observable at least five years after the discovery year - this pattern is consistent across models that don't include WGI indicators. Interestingly, the results suggest a divergence between political and economic institutions in shaping TES outcomes. Stronger political institutions (proxied by WGI indicators) tend to reinforce the TES-decreasing effect of a giant discovery. In contrast, stronger economic institutions appear to reverse this effect, generally leading to an increase in TES (see Table 5.1.2.).

Table 5.1.1. Regression analysis on TES moderated by WGI

	Dependent variable:				
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-68.265*** (16.690)	-66.578*** (16.473)	-59.413*** (17.003)	-39.640** (16.690)	-17.581 (16.797)
WGI	-0.754 (0.935)	-0.360 (0.939)	-0.299 (0.990)	-0.380 (0.997)	-0.744 (1.032)
previous discovery	0.156 (5.694)	2.368 (5.722)	2.165 (6.033)	4.537 (6.072)	5.124 (6.299)
discovery:WGI	-7.900** (3.103)	-7.509** (3.060)	-6.887** (3.157)	-5.106 (3.096)	-2.230 (3.113)
Observations	334	319	304	289	274
R2	0.116	0.123	0.094	0.042	0.015
Adjusted R2	-0.005	0.001	-0.036	-0.099	-0.135
F Statistic	9.616*** (df = 4; 293)	9.814*** (df = 4; 279)	6.899*** (df = 4; 265)	2.742** (df = 4; 251)	0.873 (df = 4; 237)

Note: “TES” depicts the TES in the year of a giant discovery, “TES1” depicts the TES in the first year after a giant discovery, and so forth. “discovery” depicts if there is a giant resource discovery. “previous discovery” depicts if there is a previous giant discovery in the past 10 years. All models control for time and country fixed effects. *p<0.1; **p<0.05; ***p<0.01.

Table 5.1.2. Regression analysis on TES moderated by CBIE

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-71.154** (28.327)	-70.544*** (26.954)	-63.935** (26.681)	-55.252** (26.935)	-44.947* (26.888)
CBIE	-41.448*** (13.345)	-45.655*** (12.993)	-49.193*** (13.190)	-47.331*** (13.602)	-47.957*** (13.916)
previous discovery	3.260 (6.182)	6.206 (5.947)	7.894 (5.956)	11.290* (6.101)	13.597** (6.192)
discovery:CBIE	93.471* (49.990)	98.470** (47.544)	96.817** (47.030)	101.158** (47.457)	93.883** (47.352)
Observations	362	349	336	323	310
R2	0.064	0.067	0.060	0.050	0.059
Adjusted R2	-0.072	-0.071	-0.082	-0.096	-0.089
F Statistic	5.403*** (df = 4; 315)	5.479*** (df = 4; 303)	4.638*** (df = 4; 291)	3.673*** (df = 4; 279)	4.204*** (df = 4; 267)

Dependent variable:					
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	-43.191 (26.749)	-27.077 (25.978)	-23.579 (24.886)	-22.988 (24.625)	-27.424 (24.130)
CBIE	-52.092*** (14.222)	-54.377*** (14.259)	-58.048*** (14.194)	-61.176*** (14.583)	-68.846*** (14.933)
previous discovery	15.353** (6.281)	17.611*** (6.241)	17.990*** (6.152)	14.918** (6.133)	12.310** (6.044)
discovery: CBIE	91.991* (47.085)	71.268 (45.702)	64.162 (43.756)	51.093 (43.301)	54.724 (42.386)
Observations	297	284	271	258	245
R2	0.070	0.091	0.103	0.089	0.101
Adjusted R2	-0.080	-0.058	-0.048	-0.069	-0.059
F Statistic	4.773*** (df = 4; 255)	6.109*** (df = 4; 243)	6.636*** (df = 4; 231)	5.379*** (df = 4; 219)	5.832*** (df = 4; 207)

Note: See Table 5.1.1.

Replacing TES with the TES Index and TES per capita yields similar results. Previous discoveries tend to increase both the TES Index and TES per capita over the long term. While political institutions consistently correlate with a decrease in the TES Index and TES per capita following a giant discovery, the effects of economic institutions vary depending on the year and specific measure. However, in about half of the models (e.g., the model using VD_rl; see Table 5.1.3.), a giant discovery actually increases the TES Index and TES per capita. Thus, no conclusive pattern can be established regarding these outcomes.

Table 5.1.3. Regression analysis on TES Index moderated by VD_rl

	Dependent variable:				
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	30.167* (15.958)	23.714* (13.594)	28.962** (12.580)	27.527** (11.611)	37.754*** (11.319)
VD_rl	-16.775 (11.738)	-6.432 (10.268)	3.303 (9.787)	11.677 (9.267)	18.524** (9.162)
previous discovery	31.381*** (6.967)	31.855*** (5.973)	30.326*** (5.567)	32.515*** (5.178)	32.946*** (5.093)
discovery:VD_rl	-236.676*** (88.138)	-184.164** (75.145)	-189.963*** (69.607)	-168.920*** (64.308)	-194.789*** (62.765)
Observations	454	439	424	409	394
R2	0.064	0.078	0.079	0.104	0.119
Adjusted R2	-0.047	-0.033	-0.034	-0.007	0.008
F Statistic	6.945*** (df = 4; 405)	8.247*** (df = 4; 391)	8.066*** (df = 4; 377)	10.554*** (df = 4; 363)	11.760*** (df = 4; 349)
	Dependent variable:				
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	45.974*** (10.960)	38.848*** (10.828)	29.485*** (10.716)	24.208** (10.639)	36.726*** (10.607)
VD_rl	25.186*** (9.020)	29.942*** (9.075)	34.141*** (9.200)	36.649*** (9.399)	37.765*** (9.688)
previous discovery	36.532*** (4.979)	36.952*** (4.972)	36.143*** (4.980)	34.713*** (4.973)	32.173*** (4.993)
discovery:VD_rl	-215.505*** (60.847)	-167.327*** (60.188)	-107.622* (59.550)	-76.756 (59.142)	-129.374** (59.170)
Observations	379	364	349	334	319
R2	0.161	0.173	0.179	0.182	0.180
Adjusted R2	0.053	0.064	0.069	0.070	0.065
F Statistic	16.047*** (df = 4; 335)	16.752*** (df = 4; 321)	16.718*** (df = 4; 307)	16.299*** (df = 4; 293)	15.281*** (df = 4; 279)

Note: “TES_index” depicts the TES Index in the year of a giant discovery, “TES_index1” depicts the TES Index in the first year after a giant discovery, and so forth; See Table 5.1.1.

5.2 Energy mix

The regression results for fossil energy (FE) supply closely mirror those for TES. A giant discovery tends to reduce FE in the initial years, mainly in models that include WGI indicators. On the other hand, previous discoveries in rest models have a lasting positive effect on FE, evident at least three years after the discovery. Institutional effects again differ: stronger political institutions correlate with reduced FE supply in the first few years, while stronger economic institutions are associated with an increase in FE supply following a giant discovery. To facilitate comparison with TES models, I present results using both WGI and CBIE measures (see Tables 5.2.1. and 5.2.2.).

Regarding FE per capita, previous discoveries generally lead to a long-term increase in supply. This finding is consistent across most models. Political institutions again show a clear negative effect on FE per capita in the context of a giant discovery, whereas the effects of economic institutions are time- and measure-dependent. Approximately half of the models indicate a

positive association between FE per capita and giant discoveries, while the other half suggest a negative one, leaving the relationship inconclusive.

Table 5.2.1. Regression analysis on FE supply moderated by WGI

	Dependent variable:				
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-2,585.274*** (626.261)	-2,541.484*** (620.237)	-2,356.733*** (637.647)	-1,511.271** (635.854)	-733.627 (639.216)
WGI	-23.425 (33.036)	-1.993 (34.051)	1.901 (35.742)	7.385 (36.209)	5.177 (37.116)
previous discovery	-57.102 (179.830)	26.855 (191.701)	104.874 (217.127)	176.636 (220.396)	185.895 (226.203)
discovery:WGI	-289.412** (115.792)	-275.415** (114.842)	-269.329** (118.391)	-190.993 (117.956)	-90.028 (118.470)
Observations	360	348	333	318	303
R2	0.114	0.122	0.098	0.039	0.013
Adjusted R2	0.0001	0.004	-0.025	-0.096	-0.129
F Statistic	10.262*** (df = 4; 318)	10.628*** (df = 4; 306)	7.941*** (df = 4; 292)	2.809** (df = 4; 278)	0.873 (df = 4; 264)
	Dependent variable:				
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,371.991** (621.787)	-628.418 (626.179)	-224.529 (622.296)	92.812 (582.381)	-707.808 (618.713)
WGI	-3.766 (37.022)	-14.875 (38.353)	-25.054 (39.567)	-17.522 (38.448)	-37.177 (42.526)
previous discovery	216.007 (225.548)	219.514 (234.083)	257.948 (241.488)	135.519 (237.189)	-39.762 (266.604)
discovery: WGI	-176.521 (115.118)	-80.668 (115.799)	-45.558 (114.950)	21.819 (107.438)	-61.153 (113.356)
Observations	288	273	258	243	228
R2	0.038	0.013	0.007	0.003	0.026
Adjusted R2	-0.105	-0.138	-0.149	-0.160	-0.139
F Statistic	2.459** (df = 4; 250)	0.777 (df = 4; 236)	0.406 (df = 4; 222)	0.175 (df = 4; 208)	1.311 (df = 4; 194)

Note: "FE" depicts the FE supply in the year of a giant discovery, "FE1" depicts the FE supply in the first year after a giant discovery, and so forth; See Table 5.1.1.

Table 5.2.2. Regression analysis on FE supply moderated by CBIE

	Dependent variable:				
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-2,976.786*** (1,096.017)	-2,938.719*** (1,027.418)	-2,717.324*** (1,006.488)	-2,354.927** (1,014.630)	-1,962.456* (1,013.150)
CBIE	-1,643.482*** (504.989)	-1,809.914*** (478.525)	-1,952.738*** (474.505)	-1,902.239*** (489.519)	-1,937.044*** (501.348)
previous discovery	141.859 (214.238)	231.283 (210.925)	321.064 (219.592)	444.703** (223.795)	513.040** (226.110)
discovery:CBIE	3,885.069** (1,928.847)	4,019.486** (1,809.971)	4,011.577** (1,775.841)	4,167.581** (1,789.266)	3,858.920** (1,785.403)
Observations	387	374	361	348	335
R2	0.069	0.077	0.072	0.057	0.062
Adjusted R2	-0.063	-0.056	-0.064	-0.084	-0.080
F Statistic	6.301*** (df = 4; 338)	6.792*** (df = 4; 326)	6.122*** (df = 4; 314)	4.557*** (df = 4; 302)	4.832*** (df = 4; 290)
	Dependent variable:				
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,958.538* (1,009.611)	-1,307.266 (987.465)	-1,112.415 (947.034)	-936.063 (922.021)	-1,390.187 (911.581)
CBIE	-2,113.363*** (510.429)	-2,199.358*** (511.716)	-2,339.561*** (504.252)	-2,435.972*** (506.975)	-2,777.216*** (520.333)
previous discovery	538.058** (228.596)	624.324*** (227.323)	682.843*** (222.273)	691.963*** (221.399)	535.017** (225.828)
discovery:CBIE	3,692.114** (1,778.340)	2,895.480* (1,738.437)	2,786.509* (1,666.378)	2,552.750 (1,621.398)	2,664.980* (1,603.826)
Observations	322	309	296	283	270
R2	0.070	0.087	0.112	0.127	0.117
Adjusted R2	-0.074	-0.057	-0.031	-0.017	-0.032
F Statistic	5.201*** (df = 4; 278)	6.318*** (df = 4; 266)	8.042*** (df = 4; 254)	8.789*** (df = 4; 242)	7.645*** (df = 4; 230)

Note: See Table 5.1.1.

When controlling for political institutions (using WGI indicators), a giant resource discovery tends to reduce renewable energy (RE) supply both immediately and in the ninth year post-discovery (see Table 5.2.3.). Stronger political institutions accelerate this decline. However, models using other institutional moderators fail to uniformly confirm this pattern.

Excluding solid biofuels from the RE (RE_exbio) provides clearer results. A giant discovery reduces RE_exbio over several years post-discovery, with stronger political institutions intensifying the decline (except the model employing GSD_rl_pe). Conversely, stronger economic institutions (proxied by EFW or EcGI) tend to mitigate the decline in RE_exbio (see Table 5.2.4.).

Previous discoveries are not significantly correlated with either RE or RE_exbio, but they are negatively associated with RE per capita. Specifically, in countries with a giant discovery within the last 10 years, RE per capita tends to decline after five years. No significant relationship is found between giant discoveries and RE_exbio per capita. However, there is a consistently positive correlation between institution quality (across various indices) and RE_exbio per capita.

An analysis of renewable energy as a share of total energy supply or consumption (i.e., RE/TES, RE_exbio/TES, and RE/TFC) reveals no significant interaction effects with giant discoveries, suggesting that giant discoveries do not meaningfully alter the composition of the energy mix.

Table 5.2.3. Regression analysis on RE supply moderated by WGI_ge

	Dependent variable:				
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-79.707*** (21.711)	-112.952*** (20.838)	-58.162*** (21.920)	-101.506*** (21.297)	-70.882*** (21.850)
WGI_ge	-14.798* (8.286)	-5.854 (8.172)	-2.633 (8.791)	-4.528 (8.648)	-9.530 (9.074)
previous discovery	9.566 (9.880)	4.754 (10.170)	-2.604 (11.710)	-3.948 (11.533)	-4.263 (12.023)
discovery:WGI_ge	-67.368*** (24.985)	-97.183*** (23.981)	-45.108* (25.246)	-72.860*** (24.468)	-50.006** (25.041)
Observations	360	348	333	318	303
R2	0.061	0.097	0.028	0.096	0.054
Adjusted R2	-0.061	-0.024	-0.105	-0.031	-0.082
F Statistic	5.121*** (df = 4; 318)	8.258*** (df = 4; 306)	2.116* (df = 4; 292)	7.359*** (df = 4; 278)	3.768*** (df = 4; 264)
	Dependent variable:				
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	-27.890 (23.328)	-27.449 (23.070)	-9.840 (24.139)	-41.517* (23.448)	-106.250*** (24.545)
WGI_ge	-13.931 (9.813)	-19.646** (9.865)	-22.833** (10.580)	-24.041** (10.665)	-24.727** (10.712)
previous discovery	-6.146 (13.095)	-6.520 (13.276)	-11.168 (14.347)	-16.615 (14.547)	-20.793 (14.931)
discovery:WGI_ge	-10.939 (26.660)	-4.234 (26.272)	17.346 (27.378)	-7.434 (26.461)	-67.911** (27.085)
Observations	288	273	258	243	228
R2	0.020	0.035	0.037	0.068	0.154
Adjusted R2	-0.125	-0.112	-0.115	-0.084	0.010
F Statistic	1.304 (df = 4; 250)	2.145* (df = 4; 236)	2.120* (df = 4; 222)	3.821*** (df = 4; 208)	8.830*** (df = 4; 194)

Note: "RE" depicts the RE supply in the year of a giant discovery, "RE1" depicts the RE supply in the first year after a giant discovery, and so forth; See Table 5.1.1.

Table 5.2.4. Regression analysis on RE_exbio supply moderated by EcGI

	Dependent variable:				
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	-60.193** (25.987)	-42.009 (26.341)	-17.664 (26.929)	-20.588 (27.252)	-12.256 (27.929)
EcGI	-0.152 (0.125)	-0.019 (0.130)	-0.040 (0.136)	-0.060 (0.141)	-0.063 (0.148)
Previous discovery	-0.043 (3.632)	-2.714 (3.806)	-3.517 (4.046)	-4.485 (4.125)	-3.853 (4.264)
discovery:EcGI	1.050** (0.504)	0.657 (0.511)	0.328 (0.522)	0.230 (0.528)	0.196 (0.541)
Observations	480	468	453	438	423
R2	0.020	0.014	0.003	0.013	0.003
Adjusted R2	-0.092	-0.101	-0.115	-0.106	-0.118
F Statistic	2.140* (df = 4; 430)	1.494 (df = 4; 418)	0.301 (df = 4; 404)	1.313 (df = 4; 390)	0.326 (df = 4; 376)

	Dependent variable:				
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	-110.266*** (27.920)	-95.087*** (27.553)	-103.043*** (27.110)	-92.738*** (26.706)	-75.383*** (26.562)
EcGI	-0.152 (0.153)	-0.140 (0.156)	-0.172 (0.160)	-0.190 (0.165)	-0.184 (0.173)
Previous discovery	-4.075 (4.300)	-2.900 (4.285)	-2.523 (4.263)	-3.314 (4.248)	-3.357 (4.292)
discovery:EcGI	2.100*** (0.540)	1.801*** (0.533)	1.944*** (0.524)	1.634*** (0.516)	1.308** (0.513)
Observations	408	393	378	363	348
R2	0.044	0.035	0.044	0.047	0.036
Adjusted R2	-0.075	-0.087	-0.079	-0.078	-0.093
F Statistic	4.164*** (df = 4; 362)	3.153** (df = 4; 348)	3.828** (df = 4; 334)	3.955*** (df = 4; 320)	2.863** (df = 4; 306)

Note: "RE_exbio" depicts the RE_exbio supply in the year of a giant discovery, "RE_exbio1" depicts the RE_exbio supply in the first year after a giant discovery, and so forth; See Table 5.1.1.

5.3 Energy efficiency

Among countries experiencing giant discoveries, better institutional quality is associated with an increase in energy efficiency in the first few years. In contrast, countries with previous discoveries tend to see a long-term decline in energy efficiency - this result is supported by approximately half of the models (for example, see Table 5.3.1.). When moderated by WGI indicators, a giant discovery leads to an immediate improvement in energy efficiency, but this finding is not replicated when using alternative measures of institution quality.

Table 5.3.1. Regression analysis on energy efficiency (GDP/TES) moderated by CSCI

	Dependent variable:				
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	23.415* (12.485)	24.098* (12.308)	22.124* (12.040)	17.718 (11.698)	13.853 (11.514)
CSCI	5.078** (2.209)	3.499 (2.203)	1.788 (2.183)	0.239 (2.150)	-1.222 (2.157)
Previous discovery	-24.863*** (7.716)	-27.476*** (7.648)	-25.850*** (7.527)	-26.402*** (7.363)	-25.963*** (7.301)
discovery:CSCI	17.028 (12.115)	22.221* (11.929)	25.025** (11.656)	22.661** (11.311)	22.750** (11.117)
Observations	440	425	410	395	380
R2	0.052	0.049	0.040	0.038	0.038
Adjusted R2	-0.065	-0.069	-0.082	-0.085	-0.088
F Statistic	5.308*** (df = 4; 391)	4.867*** (df = 4; 377)	3.745*** (df = 4; 363)	3.492*** (df = 4; 349)	3.336** (df = 4; 335)
	Dependent variable:				
	GDP_TES5 (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	10.202 (11.275)	5.494 (11.036)	-1.183 (10.821)	-2.700 (10.715)	2.873 (10.555)
CSCI	-3.531 (2.154)	-5.535** (2.158)	-7.740*** (2.172)	-9.390*** (2.193)	-11.060*** (2.226)
previous discovery	-28.057*** (7.209)	-27.758*** (7.124)	-27.568*** (7.056)	-27.052*** (6.950)	-27.289*** (6.863)
discovery:CSCI	24.067** (10.870)	19.946* (10.622)	13.729 (10.377)	5.557 (10.184)	17.164* (10.014)
Observations	365	350	335	320	305
R2	0.053	0.063	0.083	0.101	0.124
Adjusted R2	-0.074	-0.065	-0.046	-0.027	-0.005
F Statistic	4.457*** (df = 4; 321)	5.185*** (df = 4; 307)	6.590*** (df = 4; 293)	7.867*** (df = 4; 279)	9.356*** (df = 4; 265)

Note: "GDP_TES" depicts the GDP/TES in the year of a giant discovery, "GDP_TES1" depicts the GDP/TES in the first year after a giant discovery, and so forth; See Table 5.1.1.

5.4 Investment in renewables

There are no significant relations between giant discoveries and investment in the renewable energy sector from international society. But all models have shown the same pattern: previous discoveries in the last 10 years will first decrease the international finance flow in the renewable energy sector for at least 2 years, and after 5 years, increase the investment for one year (occasionally two years), see Table 5.4.1. This increase in investment in renewable energy is, in some models, coinciding with the increase in the proportion of investment in renewable energy.

Table 5.4.1. Regression analysis on the investment in renewable energy (SDG_7.a.1) moderated by the overall quality of institutions, including WGI, SFI, CSCI, and GSD_rl

Dependent variable:								
	discovery year (1)	one year after (2)	six years after (3)		discovery year (1)	one year after (2)	six years after (3)	
discovery	34.407 (88.945)	-1.062 (91.821)	-13.922 (100.455)		discovery	-29.400 (43.234)	21.061 (42.759)	13.662 (42.339)
WGI	7.309 (5.702)	5.205 (6.217)	-5.854 (6.153)	CSCI	1.740 (10.121)	-3.149 (9.674)	0.716 (8.421)	
previous discovery	-66.591** (26.960)	-66.385** (30.436)	83.884** (37.553)	previous discovery	-58.407** (27.590)	-70.270** (30.206)	64.045** (29.584)	
discovery:WGI	6.356 (16.406)	1.709 (16.969)	-8.674 (18.577)	discovery:CSCI	-36.991 (43.560)	37.962 (40.609)	-13.374 (40.879)	
Observations	330	315	270	Observations	340	339	334	
R2	0.027	0.020	0.026	R2	0.024	0.018	0.018	
Adjusted R2	-0.103	-0.115	-0.120	Adjusted R2	-0.107	-0.113	-0.116	
F Statistic	2.049* (df = 4; 290)	1.422 (df = 4; 276)	1.532 (df = 4; 234)	F Statistic	1.833 (df = 4; 299)	1.402 (df = 4; 298)	1.350 (df = 4; 293)	

Dependent variable:							
	discovery year (1)	one year after (2)	six years after (3)		discovery year one year after six years after (1) (2) (3)		
discovery	-21.769 (259.988)	-248.152* (139.189)	78.782 (156.278)	discovery	21.207 (107.033)	-55.530 (105.402)	72.992 (96.169)
SFI	-6.938** (3.099)	-13.216*** (3.477)	-3.499 (3.626)	GSD_rl	143.813 (127.207)	85.347 (132.642)	-184.168 (128.545)
previous discovery	-61.225** (28.278)	-94.633*** (30.339)	72.755** (30.084)	previous discovery	-66.929** (26.746)	-64.154** (28.880)	66.370** (28.445)
discovery:SFI	1.313 (16.821)	14.957 (9.214)	-3.375 (10.343)	discovery:GSD_rl	-77.358 (326.862)	128.325 (325.208)	-150.802 (301.179)
Observations	285	300	330	Observations	345	345	345
R2	0.044	0.088	0.024	R2	0.026	0.017	0.026
Adjusted R2	-0.095	-0.040	-0.107	Adjusted R2	-0.102	-0.112	-0.102
F Statistic	2.847** (df = 4; 248)	6.353*** (df = 4; 262)	1.812 (df = 4; 290)	F Statistic (df = 4; 304)	2.026*	1.344	2.021*

Note: See Table 5.1.1.

For now, there are three types of correlations. First are the correlations drawn from giant discovery and moderators; they are causal and have a strong practical implication. A giant discovery will cause the TES and FE supply to decrease in the first few years after the discovery. A better performance of WGI indicators will reinforce this trend, while economic institutions will remain opposite to the effect of a giant resource discovery. Given a giant discovery, the overall quality of institutions and the quality of political institutions are negatively correlated with TES Index, TES per capita, and FE per capita; the impacts of economic institutions are contingent on the years and moderators. A giant discovery will suppress the RE and RE_exbio supply for a range of years immediately after the discovery, and better (political) institutions will exacerbate the situation. On the contrary, better economic institutions will restrain RE/Re_exbio from decreasing, given a giant discovery. Moderated by WGI indicators, the giant discovery will lead to an immediate increase in energy efficiency for the first few years. In general, better institutions will increase energy efficiency in the first years among countries with giant discoveries.

The results largely confirm the Hs - in countries with better institutions, giant discoveries will lead to fewer setbacks in green transformation compared to countries with weaker institutions. Given a giant discovery, the quality of (political) institutions is negatively correlated with TES Index, TES per capita, and FE per capita; a better institution will also increase energy efficiency in the first years (this result does not survive the robustness checks later, though). The only inconsistent result is that better (political) institutions will decrease RE and Re_exbio along with the giant discovery; though, better economic institutions will restrain RE/Re_exbio from decreasing, given a giant discovery.

Second, are the correlations drawn from previous discoveries; they are, to some degree, causal, because previous discoveries in the last 10 years are as exogenous as the giant discovery; other than that, serial correlation cannot be effectively controlled. The results extensively confirm H_L - countries with previous resource discoveries will experience a worsening in green transformation in the long term, compared to countries without recent resource discoveries. In the countries that experienced a giant discovery in the recent 10 years, there will be a sustained increase in TES, TES Index, TES per capita, FE, and FE per capita. On the other side, countries with previous resource discoveries will experience a sustained decline in RE per capita after at least 5 years. In the meantime, these countries will observe a long-term worsening of energy efficiency. Furthermore, countries with previous resource discoveries will first attract less international investment in the renewable energy sector for at least 2 years, and after 5 years, attract more investment for one year (occasionally two years).

Third are the correlations with little interpretation space. There is a lasting positive correlation between almost all institutions and RE_exbio per capita, and a lasting negative correlation between almost all institutions and RE/TFC (SDG_7.2.1) and RE/TES. For the complete set of meaningful regression results, see the Appendix.

6. Robustness check

To assess the robustness of the main findings, I conduct a series of robustness tests. First, I proxy institutional quality using corruption indices rather than the institutional variables applied in the main analysis. Second, I replace the primary dependent variables with alternative proxies related to emissions and electricity. Third, I re-estimate the models excluding potential outliers - Russia and the Baltic states.

6.1 Corruption indexes as institutional proxies

As the first robustness test, I examine whether the results hold when using corruption indicators as alternative proxies for institutional quality. Specifically, I use four measures: the *WGI Control of Corruption*, *GSoD's Absence of Corruption*, *V-Dem's Political Corruption Index*, and the *Bayesian Corruption Index* (see Table 6.1.1.). WGI's control of governance captures perceptions of the extent to which public power is exercised for private gain. It ranges from -2.5 to 2.5, with a higher value corresponding to better governance. One of the sub-attributes of GSoD, absence of corruption (scaled to range from 0 to 1), denotes the extent to which public administration does not abuse its power for personal gain. V-Dem's political corruption index

captures legislative, judicial, executive, and public sector corruption. I reversed the scale for standardization of the indicator's direction, and it ranges from 0 to 1 to run from more corrupt to less corrupt. The Bayesian Corruption Index, as a composite index of the perceived overall level of corruption, could be seen as an augmented version of WGI. According to Standaert (2015), it is closely related to the WGI as the methodology used in the construction of the BCI is similar and augmented. The BCI index values lie between 0 and 100, with an increase in the index corresponding to a rise in the level of corruption. I rescaled this measure so that higher values indicate less corruption.

Table 6.1.1. Corruption Indexes

Indicator name	Indicator ID	Dataset	Time range	Count
Political corruption index	VD_corr	Varieties of Democracy Dataset version 13	1991 - 2023	495
Control of Corruption, Estimate	WGI_cc	The Worldwide Governance Indicators	1996 - 2022	360
The Bayesian Corruption Indicator	BCI	The Bayesian Corruption Index	1984 - 2021	395
Absence of Corruption	GSD_rl_ac	Global State of Democracy	1991 - 2023	497

Note: Compiled by the author.

The findings are largely consistent with those from the main specifications. Giant discoveries are associated with a short-term decline in total energy supply (TES) and fossil energy (FE) supply, particularly in countries with higher institutional quality. Nonetheless, the immediate effects on TES per capita, and FE per capita remain somewhat ambiguous, as contradictory patterns emerge across different model specifications. Over the long run, discoveries lead to a sustained increase in TES Index, TES per capita, FE, and FE per capita. The moderating effect of institutions is also observable in the short term, where countries with better institutions often exhibit a reduction in all forms of TES and FE.

The results for renewable energy are broadly in line with previous findings. Giant discoveries continue to reduce the share of renewable energy (RE) and renewable energy excluding biofuels (RE_exbio), except for the models employing GSD indicators. The negative correlation between the institution in the interaction term and RE and RE_exbio is confirmed. For countries with prior discoveries, the results show a consistent, long-term decline in RE per capita and worsening energy efficiency. However, the earlier observed positive effect of giant discoveries on energy efficiency disappears when corruption indicators are used as moderators. In line with the main findings, the investment dynamics in renewable energy (SDG_7.a.1) are also robust: an initial decline is followed by a temporary increase around five years after it.

6.2 Alternative dependent variables

In the second robustness check, I test whether the results hold when alternative dependent variables are used. Specifically, I substitute the main energy indicators with various measures related to carbon emissions and electricity production (see Table 6.2.1.). Fossil energy supply can be replaced by GHG, which presents total greenhouse gas emissions from fuel combustion, including CO₂, CH₄, and N₂O, expressed in kilotons (kt) of CO₂ equivalent (CO₂eq). Additionally, the carbon footprint from the ecological footprint provides another solution to

estimating CO₂ emissions. It measures CO₂ emissions associated with fossil fuel consumption by estimating biologically productive areas necessary for absorbing this CO₂. CO₂/TES (t CO₂ per TJ) depicts the amount of CO₂ released for one unit of TES, indicating the level of fossil energy share of the energy supply. It is calculated using the total CO₂ emissions from fuel combustion. Similar to energy efficiency, carbon efficiency GDP/CO₂ (2015 USD PPP per kg CO₂) is computed using the total CO₂ emissions from fuel combustion and GDP at purchasing power parities (PPP) of 2015 USD.

On the other hand, most renewable energy is transformed into electricity. The change of electricity source reflects the change of energy structure more sensitively. Therefore, I use electricity generation and capacity to test previous results. IEA reports data on total electricity generation (TEG), which shows the total amount of electricity generated by power plants, separated into electricity plants and CHP plants, expressed in GWh. Output of electricity produced from renewable sources (Re_gene) includes electricity from hydro, geothermal, solar, wind, tide, wave, biofuels, and waste. Renewable electricity excluding solid biofuels (Re_exbio) takes out electricity from biofuels and waste. I calculated “electricity efficiency” by GDP/TEG (2021 USD PPP per kWh), imitating energy efficiency and carbon efficiency; data on GDP at PPP (constant 2021 international dollars) is extracted from the World Bank.

In addition to electricity generation (GWh), IRENA publishes detailed statistics on installed capacity of renewable electricity (Re_capa, MW) from 2000. Considering most post-Soviet countries have no off-grid electricity records, I only generated data on on-grid electricity. Electricity generation includes the electricity self-consumed in energy industries, so it is not net electricity generation. Electricity installed capacity is the maximum active power that can be supplied continuously at the point of outlet. Indicator SDG_7.b.1 reported by IRENA records installed renewable energy-generating capacity in watts per capita. I calculated renewable electricity generation in kWh per capita.

Table 6.2.1. Alternative dependent variables

Green transformation / Indicators	Energy	Emission	Electricity
Energy mix	FE	GHG, Carbon Footprint	
	Quantity	RE	Re_gene, Re_capa
		RE_exbio	Re_exbio_gene
	Quantity per capita	FE/cap	CO2/cap
		RE/cap	Re_gene/cap, Re_capa/cap (SDG 7.b.1)
		RE_exbio/cap	Re_exbio_gene/cap
	Proportion	FE/TES	CO2/TES
		RE/TFC (SDG_7.2.1), RE/TES	Re/TEG
		RE_exbio/TES	Re_exbio/TEG
Energy efficiency	GDP(PPP)/TES (1/SDG_7.3.1)	GDP (PPP)/CO2	GDP (PPP)/TEG

Note: Compiled by the author.

The findings remain largely consistent. When moderated by WGI institutional quality indicators, a giant discovery tends to reduce GHG emissions in the short term. While political institutions appear to have limited influence on emissions levels, economic institutions often correlate with increased emissions. In contrast, countries with prior discoveries experience persistent increases in GHG emissions and a growing carbon footprint over time. Institutions generally help to curb emissions in the short term following a giant discovery.

For electricity generation, the results confirm that renewable electricity generation and capacity decline after a discovery, particularly in countries with better (political) institutions. Conversely, economic institutions such as EFW and EcGI tend to promote renewable electricity development. Renewable electricity per capita and SDG_7.b.1 exhibit inconsistent or weak responses to discoveries, not matching previous results.

The carbon intensity of the energy mix, as well as the share of renewables in electricity generation (Re/TEG and Re_exbio/TEG), remains largely unaffected by discoveries, suggesting that no significant structural transformation of the energy system occurs in response to the resource shock. Prior discoveries are consistently associated with long-term reductions in carbon efficiency, just like prior discoveries are consistently associated with long-term reductions in energy efficiency, but electricity efficiency appears not to be significantly correlated with giant discoveries. Unfortunately, carbon efficiency and electricity efficiency do not appear to be significantly shaped by institutional quality, given a giant discovery.

6.3 Excluding outliers: Russia and the Baltic states

In the third robustness check, I assess whether the results are driven by outliers, specifically, Russia and the Baltic states (Estonia, Latvia, and Lithuania). As explained in the literature review chapter, the short-term effect of a giant resource discovery probably stems from news shock. Russia and its predecessor have had giant gas and oil discoveries almost every year in history. Therefore, Russia, due to its frequency of discoveries, may experience diminishing marginal effects from additional discoveries in terms of shock level. The three Baltic countries have sound democratic systems, in which fair and free elections are regularly held. This feature differentiates them from other transition economies. As clarified in the background chapter, the three Baltic countries, as part of the EU, are obliged to adhere to the EU green policy and regulations. Therefore, the data from the Baltic may be partially biased. Considering that there are no giant gas and oil discoveries in the Baltic countries, their absence is not vital either. I run the regression using all moderators measuring the institution quality, but take out EFW and CBIE, because this moderator covers already insufficient sample countries. Considering the limited volume of the data, I did not test the results using data that excludes Russia and the Baltic countries at the same time.

Without Russia, the previous discovery still shows a stable impact on increasing TES, TES Index, TES per capita, FE, and FE per capita. Political and economic institutions have a clear effect on decreasing the TES Index, TES per capita, FE, and FE per capita after a giant discovery for a short period, with a few exceptions (models with PLTV_xconst, CBIE). The direct negative impact of a giant discovery on TES and FE can be reproduced, controlling for WGI indicators. This direct negative impact is, however, not as persuasive as before, because some

models reported a positive correlation. Taking out data of Russia deprives giant discoveries of the direct impact on the renewable energy (RE and RE_exbio), too. Countries with previous discoveries will decrease RE_exbio. In the year when a giant gas and oil field was discovered within the previous 10 years, there will be a sustained decrease in RE per capita after at least 5 years.

Excluding data from Estonia, Latvia, and Lithuania, giant discoveries still have a direct negative impact on TES and FE when controlling for WGI indicators, and better WGI will strengthen this trend. These results cannot be duplicated with other moderators. A major difference is that the previous discovery won't influence TES when excluding the Baltic countries. Previous discovery shows a stable impact on increasing TES Index, TES per capita, FE, and FE per capita as expected. Better institutions have a clear effect on decreasing the TES Index, TES per capita, FE, and FE per capita after a giant discovery for a short period. Taking out data from the Baltic countries deprives giant discoveries of the direct impact on the RE, similar to the situation when taking out Russia. But the giant discovery will still decrease the renewable energy excluding biofuels (RE_exbio) supply for a range of years after the discovery, and better (political) institutions will exacerbate the situation in certain years, other than GSD_rl_pe. Better economic institutions (proxied by EcGI) will restrain RE_exbio from decreasing, given a giant discovery. The impact of the previous giant discovery on RE per capita is still observable but less clear.

In terms of energy efficiency and investment, the results are not driven by outliers. Countries with previous discoveries will have a long-lasting deterioration of energy efficiency. A giant discovery will lead to an increase in energy efficiency when controlling for WGI indicators, but a decrease when using other moderators. The regression results of the investment in the renewable energy sector (SDG_7.a.1) and the proportion in the renewable energy sector match the results from the full dataset.

Overall, excluding Russia or the Baltic countries does not substantially alter the results. Without Russia, the direct influence of giant discoveries on renewable industry (RE_exbio) is transformed into a long-term influence for countries with recent discoveries. However, the change of RE is indeed introduced by Russia and the Baltic countries. The direct negative impact of giant discoveries on TES, FE, RE, and RE_exbio becomes less apparent but remains. Considering all outcomes of robustness checks, the direct impact of giant discoveries on energy efficiency and RE is not tenable. Because half of the conclusions are drawn from previous discoveries, I also test the models using giant discoveries in the previous 5 years instead of 10 years as the dummy variable. The results have shown consistent patterns as earlier outcomes; however, the influence of previous discoveries on investment disappears. For detailed results, see the spreadsheet in the Appendix.

Conclusion

This thesis examines the impact of giant oil and gas discoveries on the green transformation in post-Soviet countries using causal analysis methods. The results show that such discoveries

initially lead to a short-term decline in total energy supply (TES), likely driven by reductions in both fossil energy (FE) and renewable energy excluding biofuels (RE_exbio) supply. This initial contraction typically lasts for approximately five years. Among countries that experience a giant resource discovery, institutional quality plays a significant moderating role. Better (political) institutions are associated with further reductions in the supply of all energy types in the short term. In contrast, stronger economic institutions correlate with sustained increases in TES and renewable energy excluding biofuels. No absolute short-term correlations were found between giant discoveries and per capita indicators - TES per capita, FE per capita, renewable energy (RE) per capita, renewable energy excluding biofuels per capita - due to contradictory results across all models. The direct impact of giant resource discoveries on energy efficiency does not survive robustness checks either.

However, in the long term, giant discoveries lead to sustained increases in TES (Index), TES per capita, FE, and FE per capita. Simultaneously, they are associated with long-term declines in RE excluding biofuels, albeit with intermittent pauses. Countries with previous discoveries will also experience a RE per capita decline and a worsening energy efficiency over time. While discoveries do not directly affect international renewable energy investments in the short term, countries with gas and oil resources initially receive less investment, followed by a slight increase five years later. This is probably driven by a surge in environmental protection awareness, which appeared more recently.

Overall, the results confirm the hypothesis (H_s) that stronger institutions can moderate the negative effects of resource discoveries on green transformation, aligning with resource curse literature, where better institutions often moderate the unfavorable results brought by the energy resources. In countries with better political institutions, initial reductions in TES and FE supply are more pronounced, and better economic institutions increase RE excluding biofuels. However, these short-term moderating effects do not counteract the long-term structural consequences of resource abundance.

The results also confirm H_L , supporting theoretical frameworks such as the carbon lock-in and green paradox. New giant resource discoveries will trigger a new loop of infrastructural and institutional lock-in, consolidating the energy-institution complex. On the other hand, facing a diminishing foreign market threatened by green policies, fossil energy producers are incentivized to forward their extraction earlier to maximize their interests. New giant resource discoveries will accelerate this process further. Both theories depict an upgraded dependence on resources, as the regression results pointed out. Robustness checks - proxying green transformation by carbon emission and electricity indicators, replacing institutional moderators with corruption indices, and removing outliers - confirm the validity of the results further. Therefore, to answer my research question, giant resource discoveries do hinder the green transformation in post-Soviet countries.

Resource-rich post-Soviet countries that aim at promoting renewable energies, namely, Kazakhstan, should strengthen economic and political institutions to better absorb and manage the shocks caused by new resource discoveries, preventing further carbon lock-in and policy short-sight. International players who devoted themselves to energy transformation should

provide more targeted support for countries with recent or historical discoveries to maintain or grow renewable energy sectors.

This paper contributes to the literature by being the first to examine both the short-term and long-term impacts of giant oil and gas discoveries on green transformation, specifically in the under-researched post-Soviet space. Methodologically, the paper treats giant discoveries as exogenous events, thus allowing for a causal interpretation of their impact. However, discovery depends on exploration effort. For countries with reported discoveries, it is unclear whether the official date reflects the actual moment of discovery or the result of political decisions. For countries without such discoveries, it is equally uncertain whether this absence reflects a genuine lack of resources or a lack of willingness or capacity to explore - stemming from either low exploration intensity or limited political motivation. Fossil energy countries may strategically control the timing of discovery announcements to influence public sentiment and market expectations in favor of continued fossil fuel reliance. In contrast, countries committed to a green transformation may possess untapped reserves but choose not to invest in exploration, or may be restricted from doing so. Whether a discovery is a "natural" event or a "construct" of political and economic activity challenges the foundational assumption of exogeneity in this study.

This paper employs the institutional score in the year of the discovery in the empirical formula, hence, treating the moderator institutional quality as a static variable that will not fluctuate over time, which ignores the potential influence of giant discoveries on institutions. Constrained by time, this paper is not able to explain the direct, short-term effect of giant discoveries. The reasons for the negative relationship between giant discovery and TES, FE, and RE excluding biofuels are unclear, namely, the transmission path is still unknown. Future research can test these results using world and regional data or particular cases. Possible transmission paths should be established in anticipation of a new theory. The influence of the news shock of giant discoveries will effectively be reflected in the money flow, especially foreign direct investment, and fiscal policy responses. This could potentially influence the energy supply and energy mix immediately after a giant discovery. Besides, the oil and gas subsidies or tax reductions are also possible mediators, bridging a giant discovery and the green transformation. In future works, more nuanced attributes of giant discoveries in the dataset can be explored, for example, the discoveries' size, value, and location (onshore or offshore).

Disclaimer on AI Assistance

This paper has been prepared by the author. AI tools (ChatGPT by OpenAI) were used in a limited capacity for (i) grammar and clarity checks in the Results section, (ii) occasional wording support through Chinese-English translation, and (iii) drafting an initial version of the abstract, which was subsequently revised by the author.

References

- Abdelwahed, L., & Ohannessian, S. (2021). Giant oil discoveries and Chinese state financing: National and subnational level analyses. *Extractive Industries and Society*, 8(2), 13, Article 100878.
- Alsharif, N., & Bhattacharyya, S. (2019). Oil discovery, political institutions and economic diversification. *Scottish Journal of Political Economy*, 66(3), 459-488.
- Alsharif, N., & Bhattacharyya, S. (2024). Oil discovery, boom-bust cycle and manufacturing slowdown: Evidence from a large industry level dataset. *Review of Development Economics*, 28(2), 406-431.
- Arezki, R., Ramey, V. A., & Sheng, L. G. (2017). News shocks in open economies: Evidence from giant oil discoveries. *Quarterly Journal of Economics*, 132(1), 103-155.
- Armand, A., Coutts, A., Vicente, P. C., & Vilela, I. (2020). Does information break the political resource curse? Experimental evidence from Mozambique. *American Economic Review*, 110(11), 3431-3453.
- Auty, R. M. (1993). *Sustaining Development in Mineral Economies: The Resource Curse Thesis* (1st ed.). London: Routledge.
- Baland, J.-M., & Francois, P. (2000). Rent-seeking and resource booms. *Journal of Development Economics*, 61(2), 527-542.
- Beyer, S., & Molnar, G. (2022). *Accelerating Energy Diversification in Central and Eastern Europe*. IEA. Retrieved on 21.05.2025 from <https://www.iea.org/commentaries/accelerating-energy-diversification-in-central-and-eastern-europe>.
- Bhattacharyya, S., Conradie, L., & Arezki, R. (2017). Resource discovery and the politics of fiscal decentralization. *Journal of Comparative Economics*, 45(2), 366-382.
- Bhattacharyya, S., & Hodler, R. (2010). Natural resources, democracy and corruption. *European Economic Review*, 54(4), 608-621.
- Bhattacharyya, S., & Keller, M. (2021). Resource discovery and the political fortunes of national leaders. *Economica*, 88(349), 129-166.
- Bhattacharyya, S., & Mamo, N. (2021). Natural resources and conflict in Africa: What do the data show? *Economic Development and Cultural Change*, 69(3), 903-950.
- Boschini, A. D., Pettersson, J., & Roine, J. (2007). Resource curse or not: A question of appropriability. *The Scandinavian Journal of Economics*, 109(3), 593-617.
- Brahmbhatt, M., Canuto, O., & Vostroknutova, E. (2010). *Dealing with Dutch disease*. Economic Premise. Washington, DC: World Bank.
- Brollo, F., Nannicini, T., Perotti, R., & Tabellini, G. (2013). The Political Resource Curse. *American Economic Review*, 103(5), 1759-1796.
- Buiter, W. H., & Purvis, D. D. (1983). Oil, disinflation, and export competitiveness: A model of the "Dutch disease". In J. S. Bhandari & B. H. Putnam (Eds.), *Economic Interdependence and Flexible Exchange Rates* (pp. 222-247). Cambridge, Massachusetts: MIT University Press.
- Cavalcanti, T., Da Mata, D., & Toscani, F. (2019). Winning the oil lottery: the impact of natural resource extraction on growth. *Journal of Economic Growth*, 24(1), 79-115.
- Chisadza, C., Clance, M., Gupta, R., & Wohar, M. E. (2024). Giant oil discoveries and conflicts. *Environment Development and Sustainability*, 26(6), 15681-15710.
- Collier, P., & Hoeffer, A. (1998). On economic causes of civil war. *Oxford Economic Papers*, 50(4), 563-573.
- Collier, P., & Hoeffer, A. (2004). Greed and grievance in civil war. *Oxford Economic Papers*, 56(4), 563-595.
- Corden, W. M., & Neary, J. P. (1982). Booming sector and de-industrialisation in a small open economy. *The Economic Journal*, 92(368), 825-848.
- Cotet, A. M., & Tsui, K. K. (2013a). Oil and conflict: What does the cross-country evidence really show? *American Economic Journal-Macroeconomics*, 5(1), 49-80.
- Cotet, A. M., & Tsui, K. K. (2013b). Oil, growth, and health: What does the cross-country evidence really show? *Scandinavian Journal of Economics*, 115(4), 1107-1137.
- Cust, J., Harding, T., & Vézina, P. L. (2019). Dutch Disease resistance: Evidence from Indonesian firms. *Journal of the Association of Environmental and Resource Economists*, 6(6), 1019-1051.
- Cust, J., & Mensah, J. T. (2020). *Natural resource discoveries, citizen expectations and household decisions*. Policy Research Working Paper No. WPS 9372. World Bank. <https://hdl.handle.net/10986/34420>.
- Cust, J., & Mihalyi, D. (2017). *Evidence for a Presource Curse? Oil Discoveries, Elevated Expectations, and Growth Disappointments*. Policy Research Working Paper No. WPS 8140. World Bank. <http://documents.worldbank.org/curated/en/517431499697641884>.
- Cust, J., Mihalyi, D., & Rivera-Ballesteros, A. (2021). *Giant Oil and Gas Field Discoveries 1868-2018: An Extended Version of Horn's Giant Oil and Gas Field Discoveries Dataset for Economic Analysis*. Harvard Dataverse.

- de Vocht, F., Katikireddi, S. V., McQuire, C., Tilling, K., Hickman, M., & Craig, P. (2021). Conceptualising natural and quasi experiments in public health. *BMC Med Res Methodol*, 21(1), 32.
- DIRECTORATE-GENERAL FOR ENERGY. (2023a). *Commission, Baltic States and Poland Commit to Accelerated Baltic Grid Synchronisation with Continental Europe*. European Commission. Retrieved on 21.05.2025 from https://energy.ec.europa.eu/news/commission-baltic-states-and-poland-commit-accelerated-baltic-grid-synchronisation-continental-2023-12-19_en.
- DIRECTORATE-GENERAL FOR ENERGY. (2023b). *Renewable Energy Targets*. European Commission. Retrieved on 21.05.2025 from https://energy.ec.europa.eu/topics/renewable-energy/renewable-energy-directive-targets-and-rules/renewable-energy-targets_en.
- DIRECTORATE-GENERAL FOR ENERGY. (2025a). *Baltic States Join the European Continental Electricity Grid after Fully Disconnecting from Russian and Belarusian Networks*. European Commission. Retrieved on 21.05.2025 from https://ec.europa.eu/commission/presscorner/detail/en/ip_25_436.
- DIRECTORATE-GENERAL FOR ENERGY. (2025b). *Neighbourhood-East*. European Commission. Retrieved on 21.05.2025 from https://energy.ec.europa.eu/topics/international-cooperation/key-partner-countries-and-regions/neighbourhood-east_en.
- Eastwood, R. K., & Venables, A. J. (1982). The macroeconomic implications of a resource discovery in an open-economy. *Economic Journal*, 92(366), 285-299.
- THE FRASER INSTITUTE. (2024). *Economic Freedom of the World*. <https://efotw.org/economic-freedom/dataset?geozone=world&year=2022&min-year=2&max-year=0&filter=0&page=dataset>.
- ENERGY AND BIOMASS PROJECT IN MOLDOVA. (2014). *Moldova Energy and Biomass Project: A 4 Year Path*. United Nations Development Programme. <https://kun.uz/en/news/2025/04/28/uzbekistan-turns-to-china-for-new-generation-fighter-jets-amid-shifting-alliances>.
- ENERGY COMMUNITY. (2010). *Protocol Concerning the Accession of the Republic of Moldova to the Treaty Establishing the Energy Community*. Vienna: Council of the EU and the European Council. Retrieved from <https://www.consilium.europa.eu/en/documents/treaties-agreements/agreement/?id=2010018>.
- Frynas, J. G., & Buur, L. (2020). The resource curse in Africa: Economic and political effects of anticipating natural resource revenues. *Extractive Industries and Society-an International Journal*, 7(4), 1257-1270.
- Frynas, J. G., Wood, G., & Hinks, T. (2017). The resource curse without natural resources: Expectations of resource booms and their impact. *African Affairs*, 116(463), 233-260.
- GARRIGA, A. C. (2025). *Central Bank Independence Dataset, Version 3*. <https://sites.google.com/site/carogarriga/cbi-data-1?authuser=0>.
- GELB, A. H. (1988). *Oil Windfalls: Blessing or Curse?* Washington, DC: World Bank. <http://documents.worldbank.org/curated/en/536401468771314677>.
- INTERNATIONAL IDEA. (2024). *The Global State of Democracy Indices, 1975-2023*. <https://www.idea.int/democracytracker/gsod-indices>.
- GOVERNMENT OF GEORGIA. (2018). *Georgia's Updated Nationally Determined Contribution*. United Nations Framework Convention on Climate Change. Retrieved from https://unfccc.int/sites/default/files/NDC/2022-06/NDC%20Georgia_ENG%20WEB-approved.pdf.
- GOVERNMENT OF THE REPUBLIC OF ARMENIA. (2020). *Republic of Armenia Energy Sector Development Strategic Program to 2040*. United Nations ESCAP. Retrieved from <https://policy.asiapacificenergy.org/node/4402>.
- GOVERNMENT OF THE REPUBLIC OF BELARUS. (2010). *Energy Capacity Development Strategy of the Republic of Belarus*. (1180). Ministry of Foreign Affairs of the Republic of Belarus. Retrieved from https://mfa.gov.by/upload/energy_security_charter.pdf.
- GOVERNMENT OF THE REPUBLIC OF KYRGYZSTAN. (2018). *National Development Strategy of the Kyrgyz Republic for the Period of 2018-2040*. Retrieved from <https://www.fao.org/faolex/results/details/en/c/LEX-FAOC203822/>.
- GOVERNMENT OF THE REPUBLIC OF TAJIKISTAN. (2023). *National Development Strategy of the Republic of Tajikistan for the Period up to 2030*. Ministry of Economic Development and Trade of the Republic of Tajikistan. Retrieved from <https://medt.tj/en/strategy-and-programmes/nds2030>.
- Gylfason, T., Herbertsson, T. T., & Zoega, G. (1999). A mixed blessing: Natural resources and economic growth. *Macroeconomic Dynamics*, 3(2), 204-225.
- Harding, T., Stefanski, R., & Toews, G. (2020). Boom goes the price: giant resource discoveries and real exchange rate appreciation. *Economic Journal*, 130(630), 1715-1728.
- Harding, T., & Venables, A. J. (2016). The implications of natural resource exports for nonresource trade. *IMF Economic Review*, 64(2), 268-302.
- Hartwell, C., Horvath, R., Horvathova, E., & Popova, O. (2022). Natural resources and income inequality in developed countries: synthetic control method evidence. *Empirical Economics*, 62(2), 297-338.
- Hayat, A., Ganiev, B., & Tang, X. L. (2013). Expectations of future income and real exchange rate movements. *Journal of Banking & Finance*, 37(4), 1274-1285.
- Hotelling, H. (1931). The economics of exhaustible resources. *Journal of Political Economy*, 39(2), 137-175.
- Humphreys, M. (2005). Natural resources, conflict, and conflict resolution: Uncovering the mechanisms. *The Journal of Conflict Resolution*, 49(4), 508-537.

- IEA. (2020a). *Belarus Energy Profile*. Paris: International Energy Agency. <https://www.iea.org/reports/belarus-energy-profile>.
- IEA. (2020b). *Ukraine Energy Profile*. Paris: International Energy Agency. <https://www.iea.org/reports/ukraine-energy-profile>.
- IEA. (2023a). *Armenia Energy Profile*. Paris: International Energy Agency. <https://www.iea.org/reports/armenia-energy-profile>.
- IEA. (2023b). *Estonia 2023*. Paris: International Energy Agency. <https://www.iea.org/reports/estonia-2023>.
- IEA. (2023c). *Net Zero by 2050*. Paris: International Energy Agency. <https://www.iea.org/reports/net-zero-by-2050>.
- IEA. (2025). *EU4Energy*. Retrieved on 22.05.2025 from <https://www.iea.org/programmes/eu4energy>.
- International Renewable Energy Agency. (2025). *IRENA Stats Tool*. <https://www.irena.org/Data/Downloads/Tools>.
- Katovich, E. S. (2024). Winning and losing the resource lottery: Governance after uncertain oil discoveries. *Journal of Development Economics*, 166, 14, Article 103204.
- Keynes, J. M. (1936). *The General Theory of Employment, Interest, and Money*. International Relations and Security Network.
- KOF Swiss Economic Institute. (2023). *KOF Globalisation Index*. <https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html>.
- Kosowska, K., & Kosowski, P. (2022). Energy security of hydropower producing countries - The cases of Tajikistan and Kyrgyzstan. *Energies*, 15(21), 7822.
- Kumar, M. S., & Osband, K. (1991). *Energy Pricing in the Soviet Union*. Working Paper No. 1991/125. International Monetary Fund.
- KUN.UZ. (2023a). *Turkmenistan Resumes Gas Exports to Uzbekistan*. KUN.UZ. Retrieved on 21.05.2025 from <https://kun.uz/en/54230050>.
- KUN.UZ. (2023b). *Turkmenistan to Supply up to 2 Billion Cubic Meters of Gas to Uzbekistan per Year*. KUN.UZ. Retrieved on 21.05.2025 from <https://kun.uz/en/16802656#>.
- Lawler, P. (1991). Aggregate demand and aggregate supply effects of a resource discovery in a simple macroeconomic model. *Manchester School of Economic and Social Studies*, 59(3), 227-243.
- Lei, Y. H., & Michaels, G. (2014). Do giant oilfield discoveries fuel internal armed conflicts? *Journal of Development Economics*, 110, 139-157.
- Li, N. (2025). *Can Kazakhstan Succeed in Its Transition Toward Clean Energy?* The Diplomat. Retrieved on 21.05.2025 from <https://thediplomat.com/2025/02/can-kazakhstan-succeed-in-its-transition-toward-clean-energy/>.
- Macuane, J. J., Buur, L., & Monjane, C. M. (2018). Power, conflict and natural resources: The Mozambican crisis revisited. *African Affairs*, 117(468), 415-438.
- Mamo, N., Bhattacharyya, S., & Moradi, A. (2019). Intensive and extensive margins of mining and development: Evidence from Sub-Saharan Africa. *Journal of Development Economics*, 139, 28-49.
- Mansoorian, A. (1991). Resource discoveries and excessive external borrowing. *Economic Journal*, 101(409), 1497-1509.
- Masi, T., & Ricciuti, R. (2019). The heterogeneous effect of oil discoveries on democracy. *Economics & Politics*, 31(3), 374-402.
- Mehlum, H., Moene, K., & Torvik, R. (2006). Institutions and the resource curse. *The Economic Journal*, 116(508), 1-20.
- Mhuru, R. M., Daglish, T., & Geng, H. (2022). Oil discoveries and innovation. *Energy Economics*, 110, 13, Article 105997.
- Mihalyi, D., & Scurfield, T. (2021). How Africa's prospective petroleum producers fell victim to the presource curse. *Extractive Industries and Society-an International Journal*, 8(1), 220-232.
- Ministry of Economy and Sustainable Development of Georgia, & Ministry of Environmental Protection and Agriculture of Georgia. (2023). *Integrated National Energy and Climate Plan of Georgia*. Energy Community. Retrieved from <https://www.energy-community.org/dam/jcr:4dfd3e00-78c0-47a8-a2d9-01ec62459010>.
- Nearly, J. P., & Vanwijnbergen, S. (1984). Can an oil discovery lead to a recession: A comment on Eastwood and Venables. *Economic Journal*, 94(374), 390-395.
- O'Reilly, C., & Murphy, R. H. (2022). An index measuring state capacity, 1789-2018. *Economica*, 89(355), 713-745.
- O'Reilly, C., & Murphy, R. H. (2017). Exogenous resource shocks and economic freedom. *Comparative Economic Studies*, 59(3), 243-260.
- Okada, K., & Samreth, S. (2021). Oil bonanza and the composition of government expenditure. *Economics of Governance*, 22(1), 23-46.
- Orre, A., & Rønning, H. (2017). *Mozambique: A Political Economy Analysis*. <https://www.cmi.no/publications/6366-mozambique-a-political-economy-analysis>.

- Oziel, C. (2023). *Russia Starts Gas Supplies to Uzbekistan via Kazakhstan*. Reuters. Retrieved on 21.05.2025 from <https://www.reuters.com/markets/commodities/russia-starts-gas-supplies-uzbekistan-via-kazakhstan-2023-10-07/>.
- Paler, L., Springman, E., Grossman, G., & Pierskalla, J. (2023). Oil discoveries and political windfalls: evidence on presidential support in Uganda. *Political Science Research and Methods*, 11(4), 903-912.
- Perez-Sebastian, F., Raveh, O., & van der Ploeg, F. (2021). Oil discoveries and protectionism: Role of news effects. *Journal of Environmental Economics and Management*, 107, 27, Article 102425.
- Pigou, A. C. (1927). *Industrial Fluctuations* (1st ed.). London: Routledge.
- Center for Systemic Peace. (2018). *Polity5 Project, Political Regime Characteristics and Transitions, 1800-2018*. <https://www.systemicpeace.org/inscrdata.html>.
- Putz, C. (2024). *Russian Gas Supplies to Uzbekistan Set to Grow*. The Diplomat. Retrieved on 21.05.2025 from <https://thediplomat.com/2024/03/russian-gas-supplies-to-uzbekistan-set-to-grow/>.
- Remler, D. K., & Van Ryzin, G. G. (2021). *Research Methods in Practice: Strategies for Description and Causation*. London: Sage Publications.
- Robinson, J. A., Torvik, R., & Verdier, T. (2006). Political foundations of the resource curse. *Journal of Development Economics*, 79(2), 447-468.
- Ross, M. L. (2004). What do we know about natural resources and civil war? *Journal of Peace Research*, 41(3), 337-356.
- Roux, J., van der Spuy, D., & Singh, V. (2004). *Deepwater Drilling on the Way off South Africa*. Offshore. Retrieved on 22.05.2025 from <https://www.offshore-mag.com/geosciences/article/16756839/deepwater-drilling-on-the-way-off-south-africa>.
- Rudenko, Y. N. (1993). *Electric Power Development in the USSR*. 1st Israel - Former USSR Energy Conference. Institute of Energy Research, USSR Academy of Sciences.
- Sachs, J. D., & Warner, A. M. (1995). *Natural Resource Abundance and Economic Growth*. National Bureau of Economic Research Working Paper Series. Cambridge.
- Satubaldina, A. (2020). *Tokayev Announces Kazakhstan's Pledge to Reach Carbon Neutrality by 2060*. The Astana Times. Retrieved on 21.05.2025 from <https://astanatimes.com/2020/12/tokayev-announces-kazakhstans-pledge-to-reach-carbon-neutrality-by-2060/>.
- Seto, K. C., Davis, S. J., Mitchell, R. B., Stokes, E. C., Unruh, G., & Ürge-Vorsatz, D. (2016). Carbon lock-in: Types, causes, and policy implications. *Annual Review of Environment and Resources*, 41(Volume 41, 2016), 425-452.
- Sheng, L. G., & Zhao, H. Y. (2024). Oil shocks, external adjustment, and country portfolio. *Journal of Money Credit and Banking*, 56(7), 1705-1736.
- Sinn, H.-W. (2015). *The Green Paradox: A Supply-Side View of the Climate Problem*. CESifo Working Paper Series No. 5385. <https://ssrn.com/abstract=2621998>.
- Skalamera, M. (2022). ‘Steppe-ing’ out of Russia’s shadow: Russia’s changing ‘energy power’ in post-Soviet Eurasia. *Europe-Asia Studies*, 74(9), 1640-1656.
- Smith, A. (2002). *The Wealth of Nations*. Oxford: Bibliomania.
- Smith, B. (2015). The resource curse exorcised: Evidence from a panel of countries. *Journal of Development Economics*, 116, 57-73.
- Smith, B., & Wills, S. (2018). Left in the dark? Oil and rural poverty. *Journal of the Association of Environmental and Resource Economists*, 5(4), 865-904.
- Sobrinho, N., & Ruzzante, M. (2022). *The 'Fiscal Resource Curse': Giant Discoveries and Debt Sustainability*. IMF Working Paper No. 2022/010. International Monetary Fund.
- Spencer, P. D. (1984). The effect of oil discoveries on the British economy: Theoretical ambiguities and the consistent expectations simulation approach. *Economic Journal*, 94(375), 633-644.
- Standaert, S. (2023). *The Bayesian Corruption Index 2023 Update*. <https://users.ugent.be/~sastanda/BCI/BCI.html>.
- Center for Systemic Peace. (2018). *State Fragility Index and Matrix, 1995-2018*. <https://www.systemicpeace.org/inscrdata.html>.
- Toews, G., & Vézina, P. L. (2022). Resource discoveries, FDI bonanzas, and local multipliers: Evidence from Mozambique. *Review of Economics and Statistics*, 104(5), 1046-1058.
- Torvik, R. (2002). Natural resources, rent seeking and welfare. *Journal of Development Economics*, 67(2), 455-470.
- International Trade Centre. (2025). *Trade Map*. <https://www.trademap.org/Index.aspx>.
- Treisman, D. (2000). The causes of corruption: A cross-national study. *Journal of Public Economics*, 76(3), 399-457.
- Tsui, K. K. (2011). More oil, less democracy: Evidence from worldwide crude oil discoveries. *Economic Journal*, 121(551), 89-115.
- United Nations Moldova. (2018). *Energy and Biomass Project Concludes Its Activity after a 7 Years Mandate*. <https://moldova.un.org/en/15829-energy-and-biomass-project-concludes-its-activity-after-7-years-mandate>

- United Nations University World Institute for Development Economics Research. (2023). *UNU-WIDER Government Revenue Dataset*. <https://doi.org/10.35188/UNU-WIDER/GRD-2023>.
- Varieties of Democracy. (2025). *V-Dem Dataset v15*. <https://doi.org/10.23696/vdemds25>.
- Vézina, P. L. (2021). The oil nouveau-riche and arms imports. *Journal of African Economies*, 30(4), 349-369.
- Vicente, P. C. (2010). Does oil corrupt? Evidence from a natural experiment in West Africa. *Journal of Development Economics*, 92(1), 28-38.
- Wills, S. (2019). *Optimal monetary responses to news of an oil discovery*. OxCarre Working Paper. University of Oxford.
- World Bank. (2025). *World Development Indicators*. <https://databank.worldbank.org/source/world-development-indicators>.
- World Nuclear Association. (2024). *Nuclear Power in Belarus*. World Nuclear Association. Retrieved on 21.05.2025 from <https://world-nuclear.org/information-library/country-profiles/countries-a-f/belarus#:~:text=Belarus%20has%20one%20nuclear%20power,units%20were%20built%20by%20Atomanstroyexport>.
- World Bank. (2024). *Worldwide Governance Indicators*. <https://www.govindicators.org>.
- Zero Terrain. (2024). *Estonia's First Pumped Hydro Energy Storage Facility Has Issued an Invitation To Tender*. Retrieved on 21.05.2025 from <https://zeroterrain.com/press-release-estonias-first-pumped-hydro-energy-storage-facility-invitation-to-tender#:~:text=Energiasalv's%20Paldiski%20Pumped%20Hydro%20Energy,largest%20facility%20in%20the%20country>.

Appendix

Records of regression models in Chapter 5 Results

1. Energy supply

1.1. TES

	Dependent variable:				
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-68.265*** (16.690)	-66.578*** (16.473)	-59.413*** (17.003)	-39.640** (16.690)	-17.581 (16.797)
WGI	-0.754 (0.935)	-0.360 (0.939)	-0.299 (0.990)	-0.380 (0.997)	-0.744 (1.032)
pre_dis10	0.156 (5.694)	2.368 (5.722)	2.165 (6.033)	4.537 (6.072)	5.124 (6.299)
discovery:WGI	-7.900** (3.103)	-7.509** (3.060)	-6.887** (3.157)	-5.106 (3.096)	-2.230 (3.113)
Observations	334	319	304	289	274
R2	0.116	0.123	0.094	0.042	0.015
Adjusted R2	-0.005	0.001	-0.036	-0.099	-0.135
F Statistic	9.616*** (df = 4; 293)	9.814*** (df = 4; 279)	6.899*** (df = 4; 265)	2.742** (df = 4; 251)	0.873 (df = 4; 237)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model4.5,model4.6,model4.7,model4.8,model4.9, + type = "text")					

	Dependent variable:				
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	-23.193 (16.418)	-7.118 (16.447)	-9.729 (16.257)	-24.496 (15.026)	-19.391 (16.285)
WGI	-1.078 (1.045)	-1.461 (1.085)	-1.794 (1.129)	-1.530 (1.079)	-1.720 (1.208)
pre_dis10	6.638 (6.393)	6.747 (6.723)	6.536 (7.098)	0.676 (6.465)	-0.628 (6.971)
discovery:WGI	-3.143 (3.040)	-1.080 (3.042)	-1.670 (3.001)	-2.591 (2.754)	-1.690 (2.978)
Observations	259	244	229	214	199

R2	0.025	0.015	0.019	0.047	0.039
Adjusted R2	-0.128	-0.145	-0.147	-0.121	-0.139
F Statistic	1.434 (df = 4; 223)	0.797 (df = 4; 209)	0.956 (df = 4; 195)	2.252* (df = 4; 181)	1.702 (df = 4; 167)

Note:
> stargazer(model5.0,model5.1,model5.2,model5.3,model5.4,
+ type = "text")

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-7.766 (25.932)	11.688 (27.764)	11.570 (28.923)	-11.049 (31.252)	-16.786 (30.059)
SFI	1.102** (0.553)	1.004* (0.592)	0.856 (0.617)	0.552 (0.688)	0.569 (0.696)
pre_dis10	0.769 (4.809)	4.007 (5.149)	4.312 (5.364)	5.257 (5.898)	6.937 (5.786)
discovery:SFI	-0.147 (1.718)	-1.519 (1.840)	-1.383 (1.917)	0.633 (2.069)	1.379 (1.989)
Observations	360	360	360	349	334
R2	0.033	0.034	0.023	0.008	0.013
Adjusted R2	-0.092	-0.090	-0.102	-0.125	-0.121
F Statistic	2.675** (df = 4; 318)	2.805** (df = 4; 318)	1.909 (df = 4; 318)	0.606 (df = 4; 307)	0.984 (df = 4; 293)

Note:
> stargazer(model5.5,model5.6,model5.7,model5.8,model5.9,
+ type = "text")

Dependent variable:					
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	-17.087 (29.323)	4.225 (28.638)	-12.229 (28.057)	12.049 (27.154)	-3.368 (26.724)
SFI	0.784 (0.707)	0.914 (0.722)	1.084 (0.746)	1.632** (0.752)	1.401* (0.778)
pre_dis10	7.849 (5.778)	11.185* (5.802)	8.920 (5.883)	7.298 (5.712)	2.790 (5.657)
discovery:SFI	1.395 (1.939)	0.282 (1.891)	1.356 (1.851)	-0.718 (1.796)	0.168 (1.769)
Observations	319	304	289	274	259
R2	0.018	0.029	0.031	0.025	0.017
Adjusted R2	-0.119	-0.111	-0.112	-0.123	-0.138
F Statistic	1.288 (df = 4; 279)	1.955 (df = 4; 265)	2.002* (df = 4; 251)	1.535 (df = 4; 237)	0.944 (df = 4; 223)

Note:
> stargazer(model6.0,model6.1,model6.2,model6.3,model6.4,
+ type = "text")

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-1.712 (9.322)	-7.566 (8.309)	-5.345 (7.905)	-4.411 (7.776)	1.336 (7.869)
CSCI	0.883 (1.650)	0.842 (1.487)	0.507 (1.433)	0.023 (1.429)	-0.231 (1.474)
pre_dis10	2.998 (5.761)	5.092 (5.163)	5.846 (4.942)	8.283* (4.894)	9.059* (4.990)
discovery:CSCI	6.718 (9.046)	0.157 (8.054)	-1.475 (7.653)	-6.855 (7.518)	-5.905 (7.597)
Observations	440	425	410	395	380
R2	0.009	0.011	0.007	0.009	0.013
Adjusted R2	-0.113	-0.112	-0.119	-0.119	-0.116
F Statistic	0.868 (df = 4; 391)	1.048 (df = 4; 377)	0.656 (df = 4; 363)	0.753 (df = 4; 349)	1.119 (df = 4; 335)

Note:
> stargazer(model6.5,model6.6,model6.7,model6.8,model6.9,
+ type = "text")

Dependent variable:					
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	0.148	2.893	-0.198	-4.213	-5.643

	(7.909)	(7.942)	(7.849)	(7.700)	(7.584)
CSCI	-0.355 (1.511)	-0.944 (1.553)	-1.224 (1.575)	-0.880 (1.576)	-0.517 (1.599)
pre_dis10	10.764** (5.057)	11.832** (5.127)	12.130** (5.118)	10.907** (4.994)	9.741** (4.931)
discovery:CSCI	-8.062 (7.625)	-8.041 (7.644)	-10.093 (7.528)	-9.034 (7.318)	-9.678 (7.195)
Observations	365	350	335	320	305
R2	0.019	0.028	0.030	0.021	0.018
Adjusted R2	-0.113	-0.105	-0.106	-0.120	-0.127
F Statistic	1.513 (df = 4; 321)	2.189* (df = 4; 307)	2.228* (df = 4; 293)	1.484 (df = 4; 279)	1.210 (df = 4; 265)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	21.204 (22.472)	20.118 (19.919)	18.581 (18.880)	14.587 (18.532)	8.045 (18.703)
GSD_rl	-18.047 (20.429)	-21.707 (18.600)	-23.779 (17.970)	-27.436 (17.929)	-26.539 (18.419)
pre_dis10	6.733 (5.572)	7.458 (4.970)	7.607 (4.744)	8.198* (4.693)	8.271* (4.777)
discovery:GSD_rl	-90.882 (70.333)	-88.851 (62.366)	-72.528 (59.133)	-42.569 (58.070)	-5.380 (58.631)
Observations	454	439	424	409	394
R2	0.013	0.019	0.016	0.015	0.018
Adjusted R2	-0.104	-0.099	-0.104	-0.107	-0.106
F Statistic	1.304 (df = 4; 405)	1.907 (df = 4; 391)	1.523 (df = 4; 377)	1.356 (df = 4; 363)	1.579 (df = 4; 349)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	11.210 (18.745)	4.522 (18.739)	6.486 (18.449)	3.733 (17.880)	6.757 (17.547)
GSD_rl	-26.267 (18.894)	-30.608 (19.311)	-27.668 (19.445)	-23.408 (19.281)	-15.964 (19.398)
pre_dis10	9.692** (4.833)	10.109** (4.883)	10.213** (4.870)	9.261* (4.745)	8.116* (4.685)
discovery:GSD_rl	-13.835 (58.793)	16.587 (58.806)	5.274 (57.927)	-0.992 (56.317)	-13.833 (55.353)
Observations	379	364	349	334	319
R2	0.021	0.031	0.028	0.019	0.013
Adjusted R2	-0.104	-0.096	-0.102	-0.115	-0.125
F Statistic	1.826 (df = 4; 335)	2.571** (df = 4; 321)	2.182* (df = 4; 307)	1.428 (df = 4; 293)	0.946 (df = 4; 279)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4, + type = "text")					
Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	4.377 (9.716)	1.504 (8.501)	2.460 (8.088)	3.598 (8.548)	6.991 (8.638)
PLTV_xconst	1.568 (1.194)	1.732* (1.044)	1.339 (0.994)	1.287 (1.063)	1.217 (1.086)
pre_dis10	5.970 (5.028)	6.114 (4.399)	6.210 (4.186)	7.177 (4.457)	8.199* (4.539)
discovery:PLTV_xconst	-2.240 (3.127)	-1.975 (2.736)	-1.586 (2.603)	-0.900 (2.749)	-0.282 (2.784)
Observations	420	420	420	409	394
R2	0.009	0.015	0.012	0.011	0.015
Adjusted R2	-0.110	-0.103	-0.107	-0.112	-0.109

F Statistic	0.865 (df = 4; 374)	1.426 (df = 4; 374)	1.092 (df = 4; 374)	0.977 (df = 4; 363)	1.366 (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
<hr/>										
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)					
-----	-----	-----	-----	-----	-----					
discovery	10.709 (8.681)	5.055 (8.711)	6.796 (8.606)	5.514 (8.320)	10.166 (8.129)					
PLTV_xconst	0.972 (1.105)	0.581 (1.125)	0.477 (1.130)	0.419 (1.117)	0.269 (1.113)					
pre_dis10	9.491** (4.602)	10.356** (4.664)	10.318** (4.663)	9.277** (4.535)	7.903* (4.457)					
discovery:PLTV_xconst	-1.485 (2.804)	1.740 (2.820)	0.524 (2.793)	-0.847 (2.722)	-3.032 (2.672)					
-----	-----	-----	-----	-----	-----					
Observations	379	364	349	334	319					
R2	0.018	0.026	0.022	0.015	0.015					
Adjusted R2	-0.108	-0.102	-0.109	-0.120	-0.122					
F Statistic	1.549 (df = 4; 335)	2.112* (df = 4; 321)	1.727 (df = 4; 307)	1.104 (df = 4; 293)	1.080 (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4,										
+ type = "text")										
<hr/>										
Dependent variable:										
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)					
-----	-----	-----	-----	-----	-----					
discovery	-48.034*** (10.493)	-52.340*** (10.330)	-44.182*** (10.728)	-22.410** (10.620)	-1.098 (10.714)					
WGI_ge	1.400 (4.230)	2.255 (4.220)	2.593 (4.483)	1.404 (4.501)	1.266 (4.621)					
pre_dis10	-1.276 (5.634)	1.468 (5.628)	1.135 (5.946)	3.116 (6.008)	3.391 (6.221)					
discovery:WGI_ge	-26.673** (12.121)	-31.986*** (11.907)	-26.514** (12.341)	-11.831 (12.188)	6.427 (12.260)					
-----	-----	-----	-----	-----	-----					
Observations	334	319	304	289	274					
R2	0.108	0.126	0.093	0.034	0.011					
Adjusted R2	-0.014	0.004	-0.037	-0.108	-0.139					
F Statistic	8.888*** (df = 4; 293)	10.059*** (df = 4; 279)	6.812*** (df = 4; 265)	2.217* (df = 4; 251)	0.688 (df = 4; 237)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)					
-----	-----	-----	-----	-----	-----					
discovery	-8.702 (10.573)	0.604 (10.646)	4.848 (10.765)	-29.034*** (10.499)	-24.259** (11.481)					
WGI_ge	-1.073 (4.677)	-3.010 (4.889)	-2.426 (5.074)	-1.363 (4.699)	-1.699 (5.225)					
pre_dis10	5.107 (6.343)	5.698 (6.674)	4.517 (7.080)	1.007 (6.381)	-0.479 (6.896)					
discovery:WGI_ge	-2.110 (12.057)	2.864 (12.090)	7.522 (12.088)	-22.277* (11.592)	-16.946 (12.600)					
-----	-----	-----	-----	-----	-----					
Observations	259	244	229	214	199					
R2	0.015	0.007	0.007	0.052	0.036					
Adjusted R2	-0.139	-0.154	-0.162	-0.116	-0.142					
F Statistic	0.856 (df = 4; 223)	0.378 (df = 4; 209)	0.321 (df = 4; 195)	2.458** (df = 4; 181)	1.580 (df = 4; 167)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4,										
+ type = "text")										
<hr/>										
Dependent variable:										
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)					
-----	-----	-----	-----	-----	-----					
discovery	-66.357*** (22.438)	-69.298*** (22.136)	-54.353** (22.868)	-31.537 (22.426)	4.751 (22.487)					

WGI_rl	-6.358 (4.857)	-3.981 (4.883)	-4.846 (5.115)	-4.579 (5.112)	-6.119 (5.261)
pre_dis10	-2.378 (5.610)	0.242 (5.634)	-0.074 (5.945)	2.702 (5.978)	3.474 (6.181)
discovery:WGI_rl	-34.756* (19.949)	-37.316* (19.666)	-27.258 (20.303)	-16.176 (19.895)	10.325 (19.933)

Observations 334 319 304 289 274
R2 0.108 0.117 0.087 0.036 0.016
Adjusted R2 -0.013 -0.006 -0.044 -0.106 -0.133
F Statistic 8.912*** (df = 4; 293) 9.264*** (df = 4; 279) 6.302*** (df = 4; 265) 2.359* (df = 4; 251) 0.984 (df = 4; 237)

Note:
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9,
+ type = "text")

Dependent variable:					
	TESS (1)	TES6 (2)	TEST (3)	TES8 (4)	TES9 (5)
discovery	-8.194 (22.038)	7.713 (22.093)	19.199 (22.120)	-41.474* (21.554)	-36.824 (23.332)
WGI_rl	-6.892 (5.357)	-6.150 (5.545)	-6.489 (5.647)	-3.927 (5.258)	-4.928 (5.816)
pre_dis10	4.991 (6.294)	5.601 (6.630)	4.425 (7.013)	0.296 (6.373)	-0.800 (6.864)
discovery:WGI_rl	-0.565 (19.521)	8.840 (19.554)	18.808 (19.494)	-26.938 (18.782)	-23.182 (20.283)

Observations 259 244 229 214 199
R2 0.022 0.012 0.015 0.044 0.036
Adjusted R2 -0.132 -0.149 -0.152 -0.124 -0.142
F Statistic 1.252 (df = 4; 223) 0.632 (df = 4; 209) 0.743 (df = 4; 195) 2.104* (df = 4; 181) 1.578 (df = 4; 167)

Note:
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4,
+ type = "text")

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-39.171*** (6.953)	-39.276*** (6.909)	-34.640*** (7.151)	-20.399*** (7.067)	-10.880 (7.121)
WGI_rq	-11.608*** (3.894)	-9.187** (3.963)	-9.312** (4.210)	-8.145* (4.279)	-8.813** (4.422)
pre_dis10	-1.755 (5.543)	0.775 (5.596)	0.763 (5.898)	3.314 (5.960)	4.881 (6.166)
discovery:WGI_rq	-18.029** (7.351)	-17.398** (7.288)	-16.272** (7.522)	-10.653 (7.410)	-7.213 (7.436)

Observations 334 319 304 289 274
R2 0.143 0.142 0.114 0.055 0.032
Adjusted R2 0.026 0.022 -0.013 -0.084 -0.115
F Statistic 12.214*** (df = 4; 293) 11.560*** (df = 4; 279) 8.514*** (df = 4; 265) 3.645*** (df = 4; 251) 1.975* (df = 4; 237)

Note:
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9,
+ type = "text")

Dependent variable:					
	TESS (1)	TES6 (2)	TEST (3)	TES8 (4)	TES9 (5)
discovery	-14.411** (7.016)	-4.068 (7.105)	-3.563 (7.133)	-16.489** (6.584)	-15.798** (7.155)
WGI_rq	-6.067 (4.455)	-6.279 (4.620)	-3.308 (4.797)	-0.939 (4.561)	-2.261 (5.121)
pre_dis10	6.483 (6.282)	6.462 (6.636)	5.697 (7.057)	0.099 (6.419)	-0.898 (6.906)
discovery:WGI_rq	-10.946 (7.295)	-3.668 (7.345)	-3.608 (7.300)	-7.996 (6.671)	-7.649 (7.225)

Observations 259 244 229 214 199
R2 0.035 0.016 0.008 0.039 0.033
Adjusted R2 -0.116 -0.144 -0.160 -0.131 -0.146
F Statistic 2.035* (df = 4; 223) 0.865 (df = 4; 209) 0.398 (df = 4; 195) 1.821 (df = 4; 181) 1.434 (df = 4; 167)

Note:
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4,
+ type = "text")

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-18.142 (11.245)	-13.963 (10.023)	-6.970 (9.537)	7.327 (9.384)	14.219 (9.490)
GSD_rl_pe	-3.986 (10.829)	-1.364 (9.895)	3.345 (9.664)	4.056 (9.797)	4.420 (10.225)
pre_dis10	3.187 (5.336)	4.383 (4.777)	5.396 (4.568)	7.565* (4.524)	8.830* (4.611)
discovery:GSD_rl_pe	30.618 (26.985)	17.640 (24.015)	7.911 (22.819)	-16.845 (22.420)	-22.004 (22.636)
Observations	454	439	424	409	394
R2	0.010	0.012	0.008	0.008	0.015
Adjusted R2	-0.108	-0.107	-0.113	-0.115	-0.109
F Statistic	0.993 (df = 4; 405)	1.144 (df = 4; 391)	0.733 (df = 4; 377)	0.768 (df = 4; 363)	1.308 (df = 4; 349)

Note:
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9,
+ type = "text")

Dependent variable:					
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	9.832 (9.560)	19.346** (9.588)	14.055 (9.512)	4.045 (9.377)	-1.001 (9.234)
GSD_rl_pe	3.517 (10.649)	2.896 (11.118)	2.041 (11.508)	-0.443 (11.737)	-2.652 (12.183)
pre_dis10	9.648** (4.689)	11.342** (4.760)	10.882** (4.789)	9.173* (4.681)	7.178 (4.623)
discovery:GSD_rl_pe	-8.313 (22.763)	-26.828 (22.784)	-16.147 (22.493)	-1.863 (21.966)	9.413 (21.607)
Observations	379	364	349	334	319
R2	0.016	0.028	0.023	0.014	0.011
Adjusted R2	-0.110	-0.100	-0.108	-0.120	-0.127
F Statistic	1.366 (df = 4; 335)	2.274* (df = 4; 321)	1.798 (df = 4; 307)	1.055 (df = 4; 293)	0.808 (df = 4; 279)

Note:
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4,
+ type = "text")

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-0.250 (12.641)	2.748 (11.204)	5.500 (10.628)	9.452 (10.447)	12.237 (10.552)
VD_rl	-13.858 (9.298)	-14.732* (8.463)	-13.744* (8.268)	-11.953 (8.338)	-10.495 (8.540)
pre_dis10	5.216 (5.519)	6.480 (4.923)	6.939 (4.703)	8.117* (4.659)	8.864* (4.747)
discovery:VD_rl	-40.636 (69.818)	-62.213 (61.934)	-57.910 (58.806)	-50.200 (57.861)	-36.847 (58.507)
Observations	454	439	424	409	394
R2	0.013	0.021	0.017	0.014	0.017
Adjusted R2	-0.104	-0.097	-0.103	-0.108	-0.107
F Statistic	1.314 (df = 4; 405)	2.050* (df = 4; 391)	1.623 (df = 4; 377)	1.324 (df = 4; 363)	1.539 (df = 4; 349)

Note:
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9,
+ type = "text")

Dependent variable:					
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	16.024 (10.581)	13.548 (10.612)	15.389 (10.458)	9.070 (10.124)	11.849 (9.896)
VD_rl	-8.942 (8.707)	-8.432 (8.895)	-7.531 (8.978)	-6.304 (8.944)	-3.990 (9.039)

pre_dis10	10.578** (4.807)	11.005** (4.873)	11.372** (4.860)	10.016** (4.732)	9.134* (4.658)					
discovery:VD_r1	-56.956 (58.742)	-24.999 (58.988)	-45.373 (58.116)	-35.835 (56.277)	-58.816 (55.204)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.021	0.027	0.025	0.017	0.015					
Adjusted R2	-0.104	-0.101	-0.105	-0.117	-0.122					
F Statistic	1.830 (df = 4; 335)	2.198* (df = 4; 321)	2.008* (df = 4; 307)	1.287 (df = 4; 293)	1.095 (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)					
<hr/>										
discovery	-314.411*** (62.152)	-258.147*** (61.086)	-280.826*** (63.072)	-253.871*** (66.080)	-284.450*** (63.456)					
EFW	4.851 (3.039)	6.334** (3.113)	4.137 (3.314)	4.185 (3.554)	3.380 (3.507)					
pre_dis10	-7.953 (6.471)	-5.382 (6.573)	-7.019 (7.069)	-4.664 (7.795)	-5.363 (8.002)					
discovery:EFW	49.283*** (10.872)	39.357*** (10.680)	43.895*** (11.023)	41.411*** (11.543)	47.970*** (11.079)					
<hr/>										
Observations	282	269	256	243	230					
R2	0.224	0.225	0.198	0.114	0.117					
Adjusted R2	0.102	0.101	0.066	-0.035	-0.037					
F Statistic	17.516*** (df = 4; 243)	16.761*** (df = 4; 231)	13.493*** (df = 4; 219)	6.676*** (df = 4; 207)	6.437*** (df = 4; 195)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)					
<hr/>										
discovery	-361.240*** (59.157)	-231.462*** (61.467)	-366.559*** (59.526)	-145.864** (66.709)	-264.100*** (65.695)					
EFW	1.127 (3.332)	0.794 (3.543)	-0.943 (3.457)	2.822 (3.786)	0.686 (3.822)					
pre_dis10	-6.457 (8.173)	-2.947 (9.697)	-5.891 (11.695)	-10.852 (12.210)	-13.440 (11.931)					
discovery:EFW	61.125*** (10.323)	39.493*** (10.722)	63.433*** (10.415)	23.378** (11.777)	43.825*** (11.592)					
<hr/>										
Observations	217	204	191	178	165					
R2	0.189	0.083	0.195	0.067	0.144					
Adjusted R2	0.043	-0.088	0.039	-0.123	-0.040					
F Statistic	10.665*** (df = 4; 183)	3.877*** (df = 4; 171)	9.657*** (df = 4; 159)	2.647** (df = 4; 147)	5.680*** (df = 4; 135)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)					
<hr/>										
discovery	23.080 (62.913)	14.438 (63.025)	25.774 (63.174)	7.663 (62.362)	-13.225 (59.873)					
IEF	-0.294 (0.252)	-0.432* (0.259)	-0.617** (0.264)	-0.710*** (0.265)	-0.752*** (0.261)					
pre_dis10	-3.223 (6.052)	-0.839 (6.191)	-0.667 (6.362)	2.171 (6.460)	3.940 (6.417)					
discovery:IEF	-0.835 (1.242)	-0.650 (1.244)	-0.816 (1.247)	-0.257 (1.231)	0.260 (1.182)					
<hr/>										
Observations	351	337	323	309	295					
R2	0.044	0.046	0.045	0.029	0.033					
Adjusted R2	-0.090	-0.090	-0.095	-0.116	-0.114					
F Statistic	3.506*** (df = 4; 307)	3.548*** (df = 4; 294)	3.275** (df = 4; 281)	2.027* (df = 4; 268)	2.204* (df = 4; 255)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9,										

```
+ type = "text")
```

Dependent variable:					
	TESS (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	-12.419 (58.174)	-19.693 (56.943)	-66.864 (55.898)	-17.676 (54.503)	11.005 (53.368)
IEF	-0.816*** (0.258)	-0.768*** (0.258)	-0.710*** (0.259)	-0.768*** (0.259)	-0.872*** (0.262)
pre_dis10	4.858 (6.501)	6.925 (6.704)	5.887 (7.064)	1.311 (6.889)	-1.596 (6.750)
discovery:IEF	0.238 (1.148)	0.484 (1.124)	1.424 (1.104)	0.302 (1.077)	-0.314 (1.055)
Observations	281	267	253	239	225
R2	0.042	0.046	0.046	0.042	0.059
Adjusted R2	-0.108	-0.108	-0.113	-0.123	-0.110
F Statistic	2.668** (df = 4; 242)	2.757** (df = 4; 229)	2.624** (df = 4; 216)	2.224* (df = 4; 203)	2.955** (df = 4; 190)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4,
+           type = "text")
```

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	-71.154** (28.327)	-70.544*** (26.954)	-63.935** (26.681)	-55.252** (26.935)	-44.947* (26.888)
CBIE	-41.448*** (13.345)	-45.655*** (12.993)	-49.193*** (13.190)	-47.331*** (13.602)	-47.957*** (13.916)
pre_dis10	3.260 (6.182)	6.206 (5.947)	7.894 (5.956)	11.290* (6.101)	13.597** (6.192)
discovery:CBIE	93.471* (49.990)	98.470** (47.544)	96.817** (47.030)	101.158** (47.457)	93.883** (47.352)
Observations	362	349	336	323	310
R2	0.064	0.067	0.060	0.050	0.059
Adjusted R2	-0.072	-0.071	-0.082	-0.096	-0.089
F Statistic	5.403*** (df = 4; 315)	5.479*** (df = 4; 303)	4.638*** (df = 4; 291)	3.673*** (df = 4; 279)	4.204*** (df = 4; 267)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9,
+           type = "text")
```

Dependent variable:					
	TESS (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)
discovery	-43.191 (26.749)	-27.077 (25.978)	-23.579 (24.886)	-22.988 (24.625)	-27.424 (24.130)
CBIE	-52.092*** (14.222)	-54.377*** (14.259)	-58.048*** (14.194)	-61.176*** (14.583)	-68.846*** (14.933)
pre_dis10	15.353** (6.281)	17.611*** (6.241)	17.990*** (6.152)	14.918** (6.133)	12.310** (6.044)
discovery:CBIE	91.991* (47.085)	71.268 (45.702)	64.162 (43.756)	51.093 (43.301)	54.724 (42.386)
Observations	297	284	271	258	245
R2	0.070	0.091	0.103	0.089	0.101
Adjusted R2	-0.080	-0.058	-0.048	-0.069	-0.059
F Statistic	4.773*** (df = 4; 255)	6.109*** (df = 4; 243)	6.636*** (df = 4; 231)	5.379*** (df = 4; 219)	5.832*** (df = 4; 207)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4,
+           type = "text")
```

Dependent variable:					
	TES (1)	TES1 (2)	TES2 (3)	TES3 (4)	TES4 (5)
discovery	230.863*** (32.548)	138.938*** (29.900)	101.194*** (28.697)	-4.964 (28.664)	-31.666 (28.842)
EcGI	-0.549*** (0.164)	-0.488*** (0.155)	-0.482*** (0.153)	-0.526*** (0.157)	-0.547*** (0.163)
pre_dis10	8.008	7.674*	7.905*	8.458*	9.408**

	(4.896)	(4.531)	(4.386)	(4.421)	(4.492)					
discovery:EcGI	-4.645*** (0.631)	-2.854*** (0.579)	-2.045*** (0.556)	0.140 (0.555)	0.761 (0.558)					
<hr/>										
Observations	454	439	424	409	394					
R2	0.152	0.095	0.070	0.036	0.046					
Adjusted R2	0.051	-0.013	-0.044	-0.083	-0.075					
F Statistic	18.104*** (df = 4; 405)	10.298*** (df = 4; 391)	7.085*** (df = 4; 377)	3.426*** (df = 4; 363)	4.184*** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES5 (1)	TES6 (2)	TES7 (3)	TES8 (4)	TES9 (5)					
discovery	-53.511* (28.867)	-90.854*** (28.451)	-114.441*** (27.707)	-111.268*** (26.870)	-100.311*** (26.415)					
EcGI	-0.532*** (0.171)	-0.618*** (0.177)	-0.620*** (0.188)	-0.563*** (0.183)	-0.562*** (0.187)					
pre_dis10	10.496** (4.546)	11.732** (4.534)	11.539** (4.478)	10.363** (4.385)	8.995** (4.350)					
discovery:EcGI	1.199** (0.559)	1.984*** (0.551)	2.417*** (0.536)	2.259*** (0.519)	2.025*** (0.518)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.053	0.089	0.107	0.095	0.085					
Adjusted R2	-0.069	-0.030	-0.012	-0.029	-0.043					
F Statistic	4.662*** (df = 4; 335)	7.834*** (df = 4; 321)	9.201*** (df = 4; 307)	7.687*** (df = 4; 293)	6.494*** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									

1.2. TES Index

	<hr/>				
Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-45.324** (19.635)	-39.580** (19.287)	-50.798*** (19.000)	-35.985* (18.938)	-30.237 (18.857)
WGI	1.897* (1.100)	2.627** (1.100)	3.180*** (1.106)	3.541*** (1.131)	3.395*** (1.158)
pre_dis10	14.912** (6.698)	21.402*** (6.700)	17.337** (6.741)	18.974*** (6.890)	16.574** (7.072)
discovery:WGI	-6.758* (3.650)	-6.111* (3.583)	-9.082** (3.527)	-6.264* (3.513)	-6.176* (3.494)
<hr/>					
Observations	334	319	304	289	274
R2	0.045	0.068	0.068	0.073	0.060
Adjusted R2	-0.085	-0.063	-0.066	-0.064	-0.083
F Statistic	3.489*** (df = 4; 293)	5.062*** (df = 4; 279)	4.824*** (df = 4; 265)	4.909*** (df = 4; 251)	3.785*** (df = 4; 237)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					
<hr/>					

	<hr/>				
Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-34.370* (18.895)	-23.770 (18.847)	-2.749 (18.553)	12.741 (18.257)	3.210 (17.621)
WGI	3.087** (1.203)	2.481** (1.244)	1.778 (1.289)	1.861 (1.311)	0.974 (1.307)
pre_dis10	21.776*** (7.357)	19.255** (7.704)	17.437** (8.101)	10.053 (7.855)	10.477 (7.543)
discovery:WGI	-7.858** (3.498)	-5.828* (3.486)	-2.266 (3.425)	1.252 (3.347)	-1.330 (3.223)
<hr/>					
Observations	259	244	229	214	199
R2	0.072	0.052	0.036	0.026	0.026
Adjusted R2	-0.073	-0.103	-0.127	-0.146	-0.154
F Statistic	4.344*** (df = 4; 223)	2.848** (df = 4; 209)	1.836 (df = 4; 195)	1.230 (df = 4; 181)	1.134 (df = 4; 167)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")					
<hr/>					

Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	47.572 (33.616)	60.071* (33.682)	62.616* (34.434)	60.223* (33.879)	54.490 (33.954)
SFI	-0.074 (0.717)	0.360 (0.718)	0.829 (0.734)	1.057 (0.746)	1.110 (0.787)
pre_dis10	19.770*** (6.234)	26.578*** (6.246)	23.483*** (6.386)	26.291*** (6.394)	24.227*** (6.536)
discovery:SFI	-3.833* (2.228)	-4.480** (2.232)	-4.434* (2.282)	-4.178* (2.243)	-3.437 (2.247)

Observations 360 360 360 349 334
R2 0.052 0.070 0.052 0.064 0.051
Adjusted R2 -0.071 -0.050 -0.070 -0.061 -0.078
F Statistic 4.323*** (df = 4; 318) 6.008*** (df = 4; 318) 4.386*** (df = 4; 318) 5.271*** (df = 4; 307) 3.944*** (df = 4; 293)

Note:
> stargazer(model5.5,model5.6,model5.7,model5.8,model5.9,
+ type = "text")

*p<0.1; **p<0.05; ***p<0.01

Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	57.474* (33.614)	74.211** (33.288)	53.819 (32.636)	13.177 (31.651)	24.652 (30.538)
SFI	1.093 (0.811)	0.595 (0.839)	0.494 (0.868)	0.528 (0.876)	1.498* (0.889)
pre_dis10	27.608*** (6.624)	31.305*** (6.744)	28.643*** (6.843)	20.623*** (6.658)	13.360** (6.465)
discovery:SFI	-3.300 (2.222)	-4.343** (2.198)	-2.997 (2.152)	-0.439 (2.094)	-1.046 (2.022)

Observations 319 304 289 274 259
R2 0.064 0.077 0.066 0.044 0.036
Adjusted R2 -0.067 -0.055 -0.071 -0.101 -0.115
F Statistic 4.790*** (df = 4; 279) 5.535*** (df = 4; 265) 4.458** (df = 4; 251) 2.721** (df = 4; 237) 2.100* (df = 4; 223)

Note:
> stargazer(model6.0,model6.1,model6.2,model6.3,model6.4,
+ type = "text")

*p<0.1; **p<0.05; ***p<0.01

Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-34.311*** (11.327)	-28.466*** (9.662)	-24.725*** (9.007)	-21.456** (8.393)	-15.831* (8.305)
CSCI	-5.596*** (2.004)	-2.321 (1.729)	0.078 (1.633)	1.952 (1.543)	2.723* (1.556)
pre_dis10	29.916*** (7.000)	31.758*** (6.004)	31.131*** (5.630)	34.120*** (5.282)	34.449*** (5.266)
discovery:CSCI	-31.890*** (10.991)	-27.024*** (9.365)	-27.719*** (8.720)	-26.054*** (8.115)	-26.532*** (8.019)

Observations 440 425 410 395 380
R2 0.084 0.089 0.086 0.111 0.118
Adjusted R2 -0.029 -0.024 -0.030 -0.003 0.002
F Statistic 8.919*** (df = 4; 391) 9.222*** (df = 4; 377) 8.503*** (df = 4; 363) 10.924*** (df = 4; 349) 11.159*** (df = 4; 335)

Note:
> stargazer(model6.5,model6.6,model6.7,model6.8,model6.9,
+ type = "text")

*p<0.1; **p<0.05; ***p<0.01

Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-12.964 (8.158)	-9.718 (8.084)	-5.533 (8.034)	0.267 (8.076)	-0.890 (8.061)
CSCI	3.548** (1.559)	4.397*** (1.581)	5.464*** (1.613)	6.517*** (1.653)	7.298*** (1.700)
pre_dis10	38.478*** (5.216)	39.798*** (5.219)	39.847*** (5.239)	37.848*** (5.238)	35.795*** (5.241)

discovery:CSCI	-28.885*** (7.865)	-25.768*** (7.782)	-21.031*** (7.704)	-13.574* (7.676)	-19.872*** (7.648)					
<hr/>										
Observations	365	350	335	320	305					
R2	0.154	0.170	0.181	0.186	0.192					
Adjusted R2	0.040	0.056	0.066	0.070	0.073					
F Statistic	14.591*** (df = 4; 321)	15.717*** (df = 4; 307)	16.169*** (df = 4; 293)	15.963*** (df = 4; 279)	15.720*** (df = 4; 265)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)					
<hr/>										
discovery	78.061*** (28.157)	61.354** (23.975)	68.249*** (22.193)	55.675*** (20.589)	66.628*** (20.145)					
GSD_rl	-57.240** (25.597)	-41.259* (22.387)	-26.212 (21.124)	-17.993 (19.919)	-18.800 (19.839)					
pre_dis10	33.355*** (6.981)	33.409*** (5.983)	31.818*** (5.577)	33.161*** (5.213)	33.296*** (5.145)					
discovery:GSD_rl	-278.006*** (88.124)	-217.284*** (75.065)	-225.769*** (69.509)	-178.856*** (64.514)	-194.815*** (63.151)					
<hr/>										
Observations	454	439	424	409	394					
R2	0.078	0.091	0.091	0.105	0.112					
Adjusted R2	-0.031	-0.018	-0.020	-0.006	0.0002					
F Statistic	8.569*** (df = 4; 405)	9.807*** (df = 4; 391)	9.392*** (df = 4; 377)	10.671*** (df = 4; 363)	11.016*** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)					
<hr/>										
discovery	73.686*** (19.649)	52.555*** (19.548)	27.267 (19.414)	20.109 (19.325)	42.775** (19.363)					
GSD_rl	-14.497 (19.805)	-9.954 (20.145)	-1.315 (20.461)	7.902 (20.838)	7.094 (21.406)					
pre_dis10	36.439*** (5.066)	36.092*** (5.094)	34.486*** (5.125)	33.319*** (5.129)	31.168*** (5.170)					
discovery:GSD_rl	-202.136*** (61.629)	-131.882** (61.347)	-49.464 (60.954)	-27.101 (60.867)	-87.907 (61.082)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.141	0.139	0.136	0.136	0.129					
Adjusted R2	0.030	0.026	0.021	0.019	0.007					
F Statistic	13.694*** (df = 4; 335)	12.965*** (df = 4; 321)	12.078*** (df = 4; 307)	11.578*** (df = 4; 293)	10.303*** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)					
<hr/>										
discovery	-20.015 (13.169)	-17.038 (11.107)	-5.000 (10.334)	2.174 (9.523)	17.255* (9.358)					
PLTV_xconst	-3.196** (1.618)	0.201 (1.365)	2.370* (1.270)	2.709** (1.184)	2.496** (1.177)					
pre_dis10	25.999*** (6.815)	27.403*** (5.748)	26.028*** (5.348)	28.820*** (4.965)	28.810*** (4.918)					
discovery:PLTV_xconst	5.061 (4.239)	4.468 (3.575)	1.395 (3.326)	-0.728 (3.063)	-4.178 (3.016)					
<hr/>										
Observations	420	420	420	409	394					
R2	0.058	0.069	0.070	0.097	0.099					
Adjusted R2	-0.056	-0.043	-0.041	-0.015	-0.014					
F Statistic	5.728*** (df = 4; 374)	6.955*** (df = 4; 374)	7.083*** (df = 4; 374)	9.710*** (df = 4; 363)	9.639*** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")										

Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	28.666*** (9.128)	30.382*** (9.005)	27.409*** (8.942)	30.006*** (8.862)	36.518*** (8.881)
PLTV_xconst	2.427** (1.162)	2.487** (1.162)	2.226* (1.174)	1.998* (1.189)	1.496 (1.215)
pre_dis10	32.045*** (4.839)	33.663*** (4.821)	34.107*** (4.845)	33.480*** (4.830)	29.607*** (4.869)
discovery:PLTV_xconst	-6.694** (2.948)	-7.129** (2.915)	-5.951** (2.902)	-7.138** (2.899)	-8.155*** (2.919)
Observations	379	364	349	334	319
R2	0.132	0.150	0.153	0.158	0.148
Adjusted R2	0.021	0.039	0.040	0.043	0.029
F Statistic	12.777*** (df = 4; 335)	14.166*** (df = 4; 321)	13.829*** (df = 4; 307)	13.722*** (df = 4; 293)	12.087*** (df = 4; 279)
Note:	*p<0.1; **p<0.05;				
***p<0.01					
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4, + type = "text")					
Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-11.243 (12.394)	-8.390 (12.272)	-14.557 (12.267)	-10.422 (12.277)	-11.587 (12.230)
WGI_ge	-4.818 (4.996)	-3.840 (5.013)	0.384 (5.126)	1.832 (5.204)	4.605 (5.275)
pre_dis10	11.595* (6.655)	18.516*** (6.686)	14.407** (6.799)	17.128** (6.946)	15.572** (7.101)
discovery:WGI_ge	-0.318 (14.317)	0.095 (14.146)	-13.636 (14.111)	-8.775 (14.090)	-17.344 (13.995)
Observations	334	319	304	289	274
R2	0.029	0.043	0.023	0.030	0.025
Adjusted R2	-0.103	-0.091	-0.117	-0.113	-0.123
F Statistic	2.207* (df = 4; 293)	3.124** (df = 4; 279)	1.554 (df = 4; 265)	1.913 (df = 4; 251)	1.534 (df = 4; 237)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9, + type = "text")					
Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-15.394 (12.257)	-12.529 (12.189)	1.033 (12.190)	1.779 (12.786)	-3.560 (12.372)
WGI_ge	6.653 (5.422)	8.898 (5.597)	9.058 (5.745)	8.631 (5.722)	2.426 (5.630)
pre_dis10	20.833*** (7.353)	18.770** (7.641)	16.730** (8.017)	10.927 (7.770)	11.397 (7.431)
discovery:WGI_ge	-28.056** (13.978)	-24.413* (13.842)	-9.935 (13.688)	-5.537 (14.116)	-16.713 (13.578)
Observations	259	244	229	214	199
R2	0.049	0.046	0.039	0.026	0.032
Adjusted R2	-0.100	-0.109	-0.124	-0.146	-0.148
F Statistic	2.871** (df = 4; 223)	2.515** (df = 4; 209)	1.977* (df = 4; 195)	1.221 (df = 4; 181)	1.366 (df = 4; 167)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4, + type = "text")					
Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-15.585 (26.474)	-8.264 (26.107)	-28.902 (25.999)	-16.611 (25.928)	-21.704 (25.790)

WGI_rl	7.402 (5.731)	7.909 (5.759)	6.337 (5.816)	4.949 (5.910)	1.541 (6.033)
pre_dis10	12.534* (6.619)	19.115*** (6.645)	14.499** (6.759)	17.023** (6.912)	15.095** (7.089)
discovery:WGI_rl	-5.090 (23.537)	-0.675 (23.195)	-23.007 (23.082)	-12.007 (23.001)	-21.220 (22.861)

Observations	334	319	304	289	274
R2	0.032	0.047	0.027	0.031	0.021
Adjusted R2	-0.101	-0.086	-0.112	-0.111	-0.128
F Statistic	2.396* (df = 4; 293)	3.460*** (df = 4; 279)	1.852 (df = 4; 265)	2.040* (df = 4; 251)	1.261 (df = 4; 237)

Note:
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9,
+ type = "text")

Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-29.808 (25.793)	-25.292 (25.530)	0.026 (25.276)	2.465 (26.303)	-9.252 (25.203)
WGI_rl	-1.616 (6.269)	-3.510 (6.408)	-5.417 (6.452)	-2.489 (6.417)	-2.175 (6.282)
pre_dis10	20.074*** (7.366)	18.576** (7.661)	17.529** (8.014)	11.761 (7.777)	11.113 (7.415)
discovery:WGI_rl	-32.436 (22.847)	-28.332 (22.596)	-7.513 (22.276)	-3.178 (22.920)	-17.020 (21.910)

Observations	259	244	229	214	199
R2	0.037	0.033	0.030	0.015	0.027
Adjusted R2	-0.114	-0.125	-0.134	-0.159	-0.154
F Statistic	2.172* (df = 4; 223)	1.767 (df = 4; 209)	1.493 (df = 4; 195)	0.684 (df = 4; 181)	1.157 (df = 4; 167)

Note:
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4,
+ type = "text")

Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-17.993** (8.362)	-15.250* (8.233)	-15.814* (8.174)	-11.795 (8.158)	-6.908 (8.145)
WGI_rq	3.892 (4.684)	8.521* (4.722)	9.922** (4.813)	11.646** (4.940)	11.011** (5.058)
pre_dis10	13.577*** (6.667)	20.572*** (6.668)	16.191** (6.742)	18.488*** (6.880)	16.094** (7.052)
discovery:WGI_rq	-10.965 (8.841)	-10.258 (8.684)	-17.120** (8.598)	-11.672 (8.554)	-12.404 (8.505)

Observations	334	319	304	289	274
R2	0.033	0.055	0.046	0.053	0.042
Adjusted R2	-0.099	-0.077	-0.091	-0.086	-0.104
F Statistic	2.476** (df = 4; 293)	4.061*** (df = 4; 279)	3.174** (df = 4; 265)	3.521*** (df = 4; 251)	2.592** (df = 4; 237)

Note:
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9,
+ type = "text")

Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-5.653 (8.085)	-3.410 (8.064)	3.577 (7.958)	4.878 (7.802)	5.582 (7.637)
WGI_rq	15.867*** (5.135)	15.619*** (5.243)	15.738*** (5.351)	17.032*** (5.405)	10.812** (5.466)
pre_dis10	21.286*** (7.240)	19.019** (7.531)	18.203** (7.873)	11.602 (7.607)	11.165 (7.371)
discovery:WGI_rq	-17.448** (8.407)	-14.401* (8.336)	-8.600 (8.143)	-2.594 (7.905)	-7.164 (7.711)

Observations	259	244	229	214	199
R2	0.079	0.071	0.069	0.065	0.047
Adjusted R2	-0.065	-0.080	-0.089	-0.100	-0.130
F Statistic	4.806*** (df = 4; 223)	3.995*** (df = 4; 209)	3.598*** (df = 4; 195)	3.170** (df = 4; 181)	2.047* (df = 4; 167)

===== Note: > stargazer(model12.0,model12.1,model12.2,model12.3,model12.4, + type = "text") =====					
Dependent variable:					

TES_index (1) TES_index1 (2) TES_index2 (3) TES_index3 (4) TES_index4 (5)					

discovery	25.723* (14.128)	25.273** (12.031)	21.985* (11.240)	14.564 (10.463)	9.034 (10.346)
GSD_rl_pe	-23.447* (13.605)	-13.428 (11.877)	-9.475 (11.390)	-10.096 (10.923)	-10.398 (11.147)
pre_dis10	28.201*** (6.704)	29.729*** (5.735)	27.376*** (5.384)	29.125*** (5.044)	27.825*** (5.027)
discovery:GSD_rl_pe	-93.209*** (33.902)	-86.132*** (28.827)	-64.908** (26.893)	-38.793 (24.997)	-6.940 (24.678)

Observations	454	439	424	409	394
R2	0.070	0.089	0.078	0.093	0.088
Adjusted R2	-0.040	-0.020	-0.034	-0.019	-0.027
F Statistic	7.645*** (df = 4; 405)	9.564*** (df = 4; 391)	7.999*** (df = 4; 377)	9.308*** (df = 4; 363)	8.375*** (df = 4; 349)
===== Note: > stargazer(model12.5,model12.6,model12.7,model12.8,model12.9, + type = "text") =====					
===== ==					
Dependent variable:					

-- TES_index5 (1) TES_index6 (2) TES_index7 (3) TES_index8 (4) TES_index9 (5)					

discovery	5.667 (10.154)	1.216 (10.038)	0.400 (9.957)	-7.131 (10.021)	-3.762 (10.127)
GSD_rl_pe	-6.982 (11.312)	-2.750 (11.640)	6.898 (12.046)	7.053 (12.543)	1.699 (13.361)
pre_dis10	30.299*** (4.980)	31.687*** (4.983)	32.972*** (5.013)	31.746*** (5.002)	27.361*** (5.070)
discovery:GSD_rl_pe	15.482 (24.178)	29.111 (23.853)	31.432 (23.546)	50.921** (23.476)	52.607** (23.695)

Observations	379	364	349	334	319
R2	0.113	0.130	0.141	0.151	0.138
Adjusted R2	-0.001	0.016	0.026	0.036	0.017
F Statistic	10.641*** (df = 4; 335)	11.969*** (df = 4; 321)	12.567*** (df = 4; 307)	13.071*** (df = 4; 293)	11.153*** (df = 4; 279)
===== ==					
Note: > stargazer(model13.0,model13.1,model13.2,model13.3,model13.4, + type = "text") =====					
===== Dependent variable:					

-- TES_index (1) TES_index1 (2) TES_index2 (3) TES_index3 (4) TES_index4 (5)					

discovery	30.167* (15.958)	23.714* (13.594)	28.962** (12.580)	27.527** (11.611)	37.754*** (11.319)
VD_rl	-16.775 (11.738)	-6.432 (10.268)	3.303 (9.787)	11.677 (9.267)	18.524** (9.162)
pre_dis10	31.381*** (6.967)	31.855*** (5.973)	30.326*** (5.567)	32.515*** (5.178)	32.946*** (5.093)
discovery:VD_rl	-236.676*** (88.138)	-184.164** (75.145)	-189.963*** (69.607)	-168.920*** (64.308)	-194.789*** (62.765)

Observations	454	439	424	409	394
R2	0.064	0.078	0.079	0.104	0.119
Adjusted R2	-0.047	-0.033	-0.034	-0.007	0.008
F Statistic	6.945*** (df = 4; 405)	8.247*** (df = 4; 391)	8.066*** (df = 4; 377)	10.554*** (df = 4; 363)	11.760*** (df = 4; 349)
===== Note: > stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text") =====					
===== Dependent variable:					

-- TES_index5 (1) TES_index6 (2) TES_index7 (3) TES_index8 (4) TES_index9 (5)					

discovery	45.974*** (10.960)	38.848*** (10.828)	29.485*** (10.716)	24.208** (10.639)	36.726*** (10.607)
VD_r1	25.186*** (9.020)	29.942*** (9.075)	34.141*** (9.200)	36.649*** (9.399)	37.765*** (9.688)
pre_dis10	36.532*** (4.979)	36.952*** (4.972)	36.143*** (4.980)	34.713*** (4.973)	32.173*** (4.993)
discovery:VD_r1	-215.505*** (60.847)	-167.327*** (60.188)	-107.622* (59.550)	-76.756 (59.142)	-129.374** (59.170)

Observations	379	364	349	334	319
R2	0.161	0.173	0.179	0.182	0.180
Adjusted R2	0.053	0.064	0.069	0.070	0.065
F Statistic	16.047*** (df = 4; 335)	16.752*** (df = 4; 321)	16.718*** (df = 4; 307)	16.299*** (df = 4; 293)	15.281*** (df = 4; 279)

Note:
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4,
+ type = "text")

*p<0.1; **p<0.05; ***p<0.01

Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	247.704*** (70.295)	241.256*** (69.651)	211.978*** (68.228)	169.984** (67.136)	129.453** (64.673)
EFW	6.946** (3.437)	10.874*** (3.549)	12.751*** (3.585)	13.937*** (3.610)	16.529*** (3.574)
pre_dis10	8.868 (7.318)	13.598* (7.494)	8.554 (7.647)	8.973 (7.920)	4.867 (8.155)
discovery:EFW	-47.222*** (12.297)	-45.298*** (12.178)	-39.702*** (11.924)	-31.622*** (11.727)	-23.689** (11.292)

Observations	282	269	256	243	230
R2	0.116	0.124	0.118	0.109	0.117
Adjusted R2	-0.022	-0.017	-0.026	-0.042	-0.037
F Statistic	7.995*** (df = 4; 243)	8.150*** (df = 4; 231)	7.355*** (df = 4; 219)	6.321*** (df = 4; 207)	6.441*** (df = 4; 195)

Note:
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9,
+ type = "text")

*p<0.1; **p<0.05; ***p<0.01

Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	78.076 (64.121)	54.313 (62.899)	-2.197 (64.030)	-33.861 (68.105)	-42.548 (67.250)
EFW	13.393*** (3.612)	11.763*** (3.626)	8.674** (3.718)	7.051* (3.783)	5.453 (3.913)
pre_dis10	10.822 (8.859)	10.591 (9.923)	5.790 (12.580)	5.785 (12.465)	4.520 (12.213)
discovery:EFW	-13.879 (11.189)	-9.094 (10.972)	1.358 (11.203)	7.275 (12.023)	9.339 (11.866)

Observations	217	204	191	178	165
R2	0.080	0.064	0.038	0.035	0.039
Adjusted R2	-0.086	-0.111	-0.149	-0.162	-0.167
F Statistic	3.985*** (df = 4; 183)	2.942** (df = 4; 171)	1.592 (df = 4; 159)	1.332 (df = 4; 147)	1.373 (df = 4; 135)

Note:
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4,
+ type = "text")

*p<0.1; **p<0.05; ***p<0.01

Dependent variable:					
	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	101.214 (63.255)	94.032 (61.171)	110.945* (60.960)	70.794 (59.700)	57.027 (58.280)
IEF	0.819*** (0.253)	1.046*** (0.251)	1.049*** (0.255)	1.142*** (0.254)	1.157*** (0.254)
pre_dis10	9.311 (6.085)	15.555** (6.009)	11.168* (6.139)	12.988** (6.184)	10.115 (6.246)
discovery:IEF	-2.234* (1.249)	-2.012* (1.207)	-2.279* (1.203)	-1.459 (1.178)	-1.110 (1.150)

Observations	351	337	323	309	295
--------------	-----	-----	-----	-----	-----

R2	0.070	0.096	0.082	0.092	0.086
Adjusted R2	-0.060	-0.033	-0.052	-0.043	-0.054

F Statistic	5.813*** (df = 4; 307)	7.780*** (df = 4; 294)	6.249*** (df = 4; 281)	6.809*** (df = 4; 268)	5.985*** (df = 4; 255)
-------------	------------------------	------------------------	------------------------	------------------------	------------------------

Note:
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9,
+ type = "text")

Dependent variable:

	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	54.137 (55.553)	55.642 (53.797)	27.302 (53.366)	-0.055 (52.885)	-7.416 (51.850)
IEF	1.293*** (0.246)	1.276*** (0.244)	1.162*** (0.248)	0.899*** (0.251)	0.764*** (0.254)
pre_dis10	13.357** (6.208)	13.140** (6.334)	9.784 (6.744)	6.585 (6.685)	3.330 (6.558)
discovery:IEF	-0.950 (1.097)	-0.941 (1.062)	-0.362 (1.054)	0.113 (1.045)	0.317 (1.025)

Observations	281	267	253	239	225
R2	0.117	0.123	0.105	0.066	0.057
Adjusted R2	-0.021	-0.019	-0.045	-0.096	-0.112

F Statistic	8.046*** (df = 4; 242)	8.023*** (df = 4; 229)	6.306*** (df = 4; 216)	3.559*** (df = 4; 203)	2.871** (df = 4; 190)
-------------	------------------------	------------------------	------------------------	------------------------	-----------------------

Note:
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4,
+ type = "text")

Dependent variable:

	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-134.382*** (27.372)	-118.197*** (26.920)	-98.578*** (27.142)	-82.806*** (26.644)	-63.346** (26.393)
CBIE	-52.498*** (12.895)	-34.890*** (12.977)	-21.609 (13.418)	-12.857 (13.455)	-7.693 (13.660)
pre_dis10	25.254*** (5.973)	31.330*** (5.939)	30.404*** (6.059)	33.749*** (6.035)	32.362*** (6.078)
discovery:CBIE	221.819*** (48.304)	198.463*** (47.483)	171.398*** (47.843)	147.479*** (46.944)	123.177*** (46.481)

Observations	362	349	336	323	310
R2	0.122	0.122	0.099	0.112	0.100
Adjusted R2	-0.006	-0.008	-0.037	-0.025	-0.041

F Statistic	10.993*** (df = 4; 315)	10.572*** (df = 4; 303)	8.037*** (df = 4; 291)	8.800*** (df = 4; 279)	7.448*** (df = 4; 267)
-------------	-------------------------	-------------------------	------------------------	------------------------	------------------------

Note:
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9,
+ type = "text")

Dependent variable:

	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-47.565* (25.908)	-6.066 (25.832)	2.065 (25.536)	1.440 (25.351)	2.849 (24.907)
CBIE	-7.634 (13.774)	-9.485 (14.180)	-18.395 (14.565)	-24.477 (15.013)	-24.355 (15.415)
pre_dis10	33.148*** (6.083)	33.183*** (6.206)	35.535*** (6.313)	33.407*** (6.314)	23.704*** (6.239)
discovery:CBIE	103.385** (45.604)	29.964 (45.446)	15.749 (44.899)	13.739 (44.578)	15.514 (43.752)

Observations	297	284	271	258	245
R2	0.108	0.110	0.129	0.124	0.082
Adjusted R2	-0.036	-0.036	-0.018	-0.028	-0.082

F Statistic	7.707*** (df = 4; 255)	7.532*** (df = 4; 243)	8.586*** (df = 4; 231)	7.749*** (df = 4; 219)	4.621*** (df = 4; 207)
-------------	------------------------	------------------------	------------------------	------------------------	------------------------

Note:
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4,
+ type = "text")

Dependent variable:

	TES_index (1)	TES_index1 (2)	TES_index2 (3)	TES_index3 (4)	TES_index4 (5)
discovery	-33.088	13.143	28.551	18.697	5.102

	(42.425)	(37.065)	(34.900)	(32.471)	(31.993)
EcGI	-1.470*** (0.214)	-0.869*** (0.192)	-0.487*** (0.186)	-0.259 (0.178)	-0.052 (0.181)
pre_dis10	29.053*** (6.382)	29.875*** (5.617)	27.397*** (5.334)	29.308*** (5.008)	28.262*** (4.983)
discovery:EcGI	0.545 (0.822)	-0.346 (0.718)	-0.576 (0.676)	-0.352 (0.629)	0.026 (0.619)
Observations	454	439	424	409	394
R2	0.143	0.111	0.080	0.090	0.085
Adjusted R2	0.041	0.004	-0.032	-0.023	-0.030
F Statistic	16.846*** (df = 4; 405)	12.189*** (df = 4; 391)	8.199*** (df = 4; 377)	8.986*** (df = 4; 363)	8.111*** (df = 4; 349)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	TES_index5 (1)	TES_index6 (2)	TES_index7 (3)	TES_index8 (4)	TES_index9 (5)
discovery	-5.698 (31.257)	-15.228 (30.755)	-23.528 (30.262)	-26.055 (29.948)	-17.319 (29.923)
EcGI	0.083 (0.185)	0.185 (0.191)	0.293 (0.197)	0.398* (0.203)	0.556*** (0.212)
pre_dis10	30.725*** (4.923)	31.891*** (4.901)	32.131*** (4.891)	31.015*** (4.888)	26.524*** (4.928)
discovery:EcGI	0.329 (0.605)	0.525 (0.595)	0.689 (0.585)	0.731 (0.579)	0.636 (0.578)
Observations	379	364	349	334	319
R2	0.112	0.131	0.145	0.153	0.149
Adjusted R2	-0.002	0.017	0.031	0.037	0.030
F Statistic	10.601*** (df = 4; 335)	12.084*** (df = 4; 321)	13.032*** (df = 4; 307)	13.199*** (df = 4; 293)	12.177*** (df = 4; 279)
Note:	*p<0.1; **p<0.05; ***p<0.01				

1.3. TES per capita

	Dependent variable:				
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)
discovery	-1.226*** (0.317)	-1.094*** (0.304)	-1.429*** (0.310)	-0.788** (0.306)	-0.537* (0.317)
WGI	0.013 (0.018)	0.029* (0.017)	0.041** (0.018)	0.046** (0.018)	0.041** (0.019)
pre_dis10	0.360*** (0.108)	0.496*** (0.106)	0.390*** (0.110)	0.422*** (0.111)	0.335*** (0.119)
discovery:WGI	-0.185*** (0.059)	-0.169*** (0.057)	-0.256*** (0.057)	-0.136** (0.057)	-0.115* (0.059)
Observations	334	319	304	289	274
R2	0.090	0.122	0.112	0.093	0.055
Adjusted R2	-0.034	-0.001	-0.015	-0.041	-0.089
F Statistic	7.287*** (df = 4; 293)	9.692*** (df = 4; 279)	8.355*** (df = 4; 265)	6.411*** (df = 4; 251)	3.422*** (df = 4; 237)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					

	Dependent variable:				
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)
discovery	-0.652** (0.310)	-0.350 (0.311)	0.058 (0.303)	0.372 (0.287)	0.140 (0.297)
WGI	0.030 (0.020)	0.022 (0.021)	0.014 (0.021)	0.022 (0.021)	-0.001 (0.022)

	(0.121)	(0.127)	(0.132)	(0.124)	(0.127)					
discovery:WGI	-0.157*** (0.057)	-0.098* (0.058)	-0.017 (0.056)	0.064 (0.053)	0.006 (0.054)					
<hr/>										
Observations	259	244	229	214	199					
R2	0.074	0.042	0.021	0.018	0.008					
Adjusted R2	-0.072	-0.114	-0.145	-0.155	-0.176					
F Statistic	4.440*** (df = 4; 223)	2.306* (df = 4; 209)	1.039 (df = 4; 195)	0.839 (df = 4; 181)	0.347 (df = 4; 167)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)					
<hr/>										
discovery	1.059* (0.560)	1.353** (0.555)	1.431** (0.566)	1.252** (0.560)	0.943* (0.562)					
SFI	0.002 (0.012)	0.005 (0.012)	0.012 (0.012)	0.016 (0.012)	0.019 (0.013)					
pre_dis10	0.389*** (0.104)	0.560*** (0.103)	0.489*** (0.105)	0.546*** (0.106)	0.463*** (0.108)					
discovery:SFI	-0.082** (0.037)	-0.098*** (0.037)	-0.098*** (0.038)	-0.084** (0.037)	-0.053 (0.037)					
<hr/>										
Observations	360	360	360	349	334					
R2	0.066	0.105	0.075	0.089	0.066					
Adjusted R2	-0.054	-0.010	-0.044	-0.033	-0.061					
F Statistic	5.636*** (df = 4; 318)	9.334*** (df = 4; 318)	6.428*** (df = 4; 318)	7.493*** (df = 4; 307)	5.191*** (df = 4; 293)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
<hr/>										
discovery	0.851 (0.553)	1.251** (0.540)	0.848 (0.528)	0.167 (0.498)	0.069 (0.477)					
SFI	0.020 (0.013)	0.014 (0.014)	0.019 (0.014)	0.023 (0.014)	0.037*** (0.014)					
pre_dis10	0.494*** (0.109)	0.572*** (0.109)	0.497*** (0.111)	0.290*** (0.105)	0.097 (0.101)					
discovery:SFI	-0.041 (0.037)	-0.067* (0.036)	-0.046 (0.035)	-0.005 (0.033)	0.004 (0.032)					
<hr/>										
Observations	319	304	289	274	259					
R2	0.084	0.102	0.080	0.045	0.045					
Adjusted R2	-0.045	-0.027	-0.056	-0.100	-0.105					
F Statistic	6.358*** (df = 4; 279)	7.517*** (df = 4; 265)	5.444*** (df = 4; 251)	2.792** (df = 4; 237)	2.639** (df = 4; 223)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)					
<hr/>										
discovery	-0.569*** (0.152)	-0.499*** (0.144)	-0.428*** (0.140)	-0.358*** (0.135)	-0.190 (0.135)					
CSCI	0.007 (0.027)	0.027 (0.026)	0.034 (0.025)	0.037 (0.025)	0.037 (0.025)					

pre_dis10	0.489*** (0.094)	0.616*** (0.090)	0.618*** (0.088)	0.674*** (0.085)	0.663*** (0.086)					
discovery:CSCI	-0.478*** (0.148)	-0.466*** (0.140)	-0.529*** (0.136)	-0.483*** (0.130)	-0.470*** (0.130)					
<hr/>										
Observations	440	425	410	395	380					
R2	0.085	0.124	0.127	0.157	0.157					
Adjusted R2	-0.027	0.015	0.017	0.048	0.046					
F Statistic	9.097*** (df = 4; 391)	13.353*** (df = 4; 377)	13.250*** (df = 4; 363)	16.211*** (df = 4; 349)	15.619*** (df = 4; 335)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model6.5,model6.6,model6.7,model6.8,model6.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
<hr/>										
discovery	-0.120 (0.133)	-0.052 (0.133)	-0.039 (0.132)	0.040 (0.133)	0.038 (0.132)					
CSCI	0.040 (0.025)	0.042 (0.026)	0.053** (0.027)	0.072*** (0.027)	0.088*** (0.028)					
pre_dis10	0.728*** (0.085)	0.736*** (0.086)	0.732*** (0.086)	0.693*** (0.086)	0.643*** (0.086)					
discovery:CSCI	-0.510*** (0.128)	-0.417*** (0.128)	-0.325** (0.127)	-0.222* (0.126)	-0.316** (0.126)					
<hr/>										
Observations	365	350	335	320	305					
R2	0.200	0.204	0.203	0.203	0.202					
Adjusted R2	0.093	0.095	0.092	0.089	0.084					
F Statistic	20.070*** (df = 4; 321)	19.637*** (df = 4; 307)	18.694*** (df = 4; 293)	17.778*** (df = 4; 279)	16.736*** (df = 4; 265)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)					
<hr/>										
discovery	1.427*** (0.363)	1.194*** (0.345)	1.498*** (0.333)	1.026*** (0.324)	1.277*** (0.323)					
GSD_rl	0.138 (0.330)	0.424 (0.322)	0.469 (0.317)	0.415 (0.313)	0.425 (0.318)					
pre_dis10	0.518*** (0.090)	0.614*** (0.086)	0.615*** (0.084)	0.637*** (0.082)	0.635*** (0.083)					
discovery:GSD_rl	-5.183*** (1.135)	-4.238*** (1.080)	-4.824*** (1.043)	-3.184*** (1.015)	-3.488*** (1.013)					
<hr/>										
Observations	454	439	424	409	394					
R2	0.107	0.135	0.142	0.148	0.155					
Adjusted R2	0.001	0.031	0.037	0.043	0.048					
F Statistic	12.106*** (df = 4; 405)	15.233*** (df = 4; 391)	15.606*** (df = 4; 377)	15.783*** (df = 4; 363)	15.952*** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
<hr/>										
discovery	1.436*** (0.317)	0.784** (0.319)	0.121 (0.316)	0.184 (0.311)	0.755** (0.312)					
GSD_rl	0.458 (0.320)	0.471 (0.329)	0.669** (0.333)	0.951*** (0.336)	1.018*** (0.345)					

pre_dis10	0.691*** (0.082)	0.663*** (0.083)	0.624*** (0.083)	0.605*** (0.083)	0.568*** (0.083)					
discovery:GSD_rl	-3.671*** (0.996)	-1.592 (1.003)	0.358 (0.991)	0.129 (0.981)	-1.491 (0.984)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.194	0.182	0.186	0.194	0.183					
Adjusted R2	0.091	0.075	0.077	0.084	0.069					
F Statistic	20.160*** (df = 4; 335)	17.848*** (df = 4; 321)	17.495*** (df = 4; 307)	17.629*** (df = 4; 293)	15.621*** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4, + type = "text")										
<hr/>										
===== ===== Dependent variable:										
<hr/>										
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)					
<hr/>										

discovery	-0.262 (0.167)	-0.241 (0.159)	0.026 (0.156)	0.093 (0.151)	0.420*** (0.151)					
PLTV_xconst	0.051** (0.021)	0.043** (0.019)	0.033* (0.019)	0.022 (0.019)	0.013 (0.019)					
pre_dis10	0.403*** (0.086)	0.512*** (0.082)	0.499*** (0.081)	0.561*** (0.079)	0.555*** (0.079)					
discovery:PLTV_xconst	0.049 (0.054)	0.059 (0.051)	-0.001 (0.050)	-0.019 (0.049)	-0.084* (0.049)					
<hr/>										

Observations	420	420	420	409	394					
R2	0.084	0.118	0.099	0.125	0.130					
Adjusted R2	-0.027	0.012	-0.010	0.017	0.021					
F Statistic	8.529*** (df = 4; 374)	12.478*** (df = 4; 374)	10.252*** (df = 4; 374)	12.975*** (df = 4; 363)	13.076*** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")										
<hr/>										
===== ===== Dependent variable:										
<hr/>										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
<hr/>										

discovery	0.649*** (0.148)	0.564*** (0.148)	0.407*** (0.147)	0.486*** (0.145)	0.645*** (0.145)					
PLTV_xconst	0.003 (0.019)	-0.007 (0.019)	-0.015 (0.019)	-0.014 (0.019)	-0.014 (0.020)					
pre_dis10	0.610*** (0.079)	0.632*** (0.079)	0.639*** (0.080)	0.619*** (0.079)	0.541*** (0.079)					
discovery:PLTV_xconst	-0.133*** (0.048)	-0.104** (0.048)	-0.069 (0.048)	-0.102** (0.047)	-0.137*** (0.048)					
<hr/>										

Observations	379	364	349	334	319					
R2	0.177	0.184	0.183	0.188	0.180					
Adjusted R2	0.071	0.077	0.074	0.077	0.066					
F Statistic	17.955*** (df = 4; 335)	18.106*** (df = 4; 321)	17.160*** (df = 4; 307)	16.929*** (df = 4; 293)	15.344*** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									

> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4,	Dependent variable:			
+ type = "text")				
=====				
	TES_cap			
	(1)	(2)	(3)	(4)
discovery	-0.485** (0.201)	-0.448** (0.194)	-0.605*** (0.201)	-0.314 (0.197)
WGI_ge	0.001 (0.081)	0.030 (0.079)	0.089 (0.084)	0.071 (0.084)
pre_dis10	0.298*** (0.108)	0.444*** (0.106)	0.328*** (0.111)	0.388*** (0.112)
discovery:WGI_ge	-0.272 (0.232)	-0.297 (0.224)	-0.651*** (0.231)	-0.295 (0.227)
Observations	334	319	304	289
R2	0.064	0.093	0.063	0.060
Adjusted R2	-0.064	-0.034	-0.072	-0.078
F Statistic	4.977*** (df = 4; 293)	7.151*** (df = 4; 279)	4.427*** (df = 4; 265)	4.025*** (df = 4; 251)
	2.197* (df = 4; 237)			
Note:	*p<0.1; **p<0.05; ***p<0.01			
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9,				
+ type = "text")				
=====				
	Dependent variable:			
	TES_cap5			
	(1)	(2)	(3)	(4)
discovery	-0.290 (0.200)	-0.165 (0.200)	0.066 (0.199)	0.023 (0.202)
WGI_ge	0.100 (0.088)	0.124 (0.092)	0.125 (0.094)	0.110 (0.098)
pre_dis10	0.382*** (0.120)	0.294** (0.126)	0.207 (0.131)	0.061 (0.123)
discovery:WGI_ge	-0.579** (0.228)	-0.415* (0.227)	-0.098 (0.223)	-0.023 (0.223)
Observations	259	244	229	214
R2	0.066	0.045	0.028	0.010
Adjusted R2	-0.081	-0.110	-0.137	-0.165
F Statistic	3.922*** (df = 4; 223)	2.485** (df = 4; 209)	1.379 (df = 4; 195)	0.478 (df = 4; 181)
	0.718 (df = 4; 167)			
Note:	*p<0.1; **p<0.05; ***p<0.01			
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4,				
+ type = "text")				
=====				
	Dependent variable:			
	TES_cap			
	(1)	(2)	(3)	(4)
discovery	-0.753* (0.428)	-0.621 (0.418)	-1.195*** (0.423)	-0.542 (0.415)
WGI_rl	0.190** (0.093)	0.226** (0.091)	0.212** (0.095)	0.185* (0.095)
pre_dis10	0.307*** (0.107)	0.446*** (0.104)	0.323*** (0.110)	0.386*** (0.111)
discovery:WGI_rl	-0.447 (0.380)	-0.377 (0.365)	-1.001*** (0.376)	-0.423 (0.368)
Observations	334	319	304	289
R2	0.076	0.110	0.074	0.071
Adjusted R2	-0.050	-0.014	-0.059	-0.066
F Statistic	6.042*** (df = 4; 293)	8.620*** (df = 4; 279)	5.293*** (df = 4; 265)	4.783*** (df = 4; 251)
	2.205* (df = 4; 237)			

Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
discovery	-0.677 (0.420)	-0.465 (0.418)	0.058 (0.412)	0.067 (0.414)	-0.261 (0.423)					
WGI_rq	0.064 (0.102)	0.072 (0.105)	0.023 (0.105)	0.099 (0.101)	0.069 (0.105)					
pre_dis10	0.368*** (0.120)	0.287** (0.125)	0.214 (0.131)	0.064 (0.122)	0.063 (0.125)					
discovery:WGI_rq	-0.759** (0.372)	-0.568 (0.370)	-0.079 (0.363)	0.017 (0.361)	-0.335 (0.368)					
Observations	259	244	229	214	199					
R2	0.055	0.038	0.019	0.008	0.015					
Adjusted R2	-0.093	-0.119	-0.147	-0.168	-0.167					
F Statistic	3.275** (df = 4; 223)	2.055* (df = 4; 209)	0.935 (df = 4; 195)	0.352 (df = 4; 181)	0.649 (df = 4; 167)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)					
discovery	-0.499*** (0.135)	-0.435*** (0.130)	-0.458*** (0.134)	-0.264** (0.132)	-0.102 (0.137)					
WGI_rq	-0.081 (0.075)	-0.001 (0.075)	0.024 (0.079)	0.046 (0.080)	-0.003 (0.085)					
pre_dis10	0.317*** (0.107)	0.463*** (0.106)	0.347*** (0.110)	0.401*** (0.112)	0.321*** (0.119)					
discovery:WGI_rq	-0.340** (0.142)	-0.318** (0.137)	-0.517*** (0.141)	-0.256* (0.139)	-0.236* (0.143)					
Observations	334	319	304	289	274					
R2	0.083	0.105	0.080	0.065	0.036					
Adjusted R2	-0.042	-0.021	-0.052	-0.072	-0.111					
F Statistic	6.624*** (df = 4; 293)	8.149*** (df = 4; 279)	5.757*** (df = 4; 265)	4.396*** (df = 4; 251)	2.208* (df = 4; 237)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
discovery	-0.086 (0.134)	-0.007 (0.135)	0.094 (0.132)	0.089 (0.125)	0.072 (0.130)					
WGI_rq	0.055 (0.085)	0.067 (0.088)	0.103 (0.089)	0.171** (0.086)	0.062 (0.093)					
pre_dis10	0.387*** (0.120)	0.299** (0.126)	0.225* (0.131)	0.059 (0.122)	0.061 (0.125)					
discovery:WGI_rq	-0.356** (0.139)	-0.240* (0.139)	-0.078 (0.135)	0.063 (0.126)	-0.060 (0.131)					
Observations	259	244	229	214	199					
R2	0.064	0.040	0.026	0.027	0.012					
Adjusted R2	-0.083	-0.116	-0.139	-0.145	-0.172					
F Statistic	3.831*** (df = 4; 223)	2.175* (df = 4; 209)	1.295 (df = 4; 195)	1.272 (df = 4; 181)	0.487 (df = 4; 167)					

===== Note: *p<0.1; **p<0.05; ***p<0.01					
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4, + type = "text")					
=====					
==					
Dependent variable:					
--					
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)

--					
discovery	0.344* (0.180)	0.378** (0.172)	0.344** (0.170)	0.230 (0.164)	0.173 (0.165)
GSD_rl_pe	-0.588*** (0.174)	-0.483*** (0.170)	-0.439** (0.172)	-0.482*** (0.171)	-0.499*** (0.178)
pre_dis10	0.418*** (0.086)	0.536*** (0.082)	0.506*** (0.081)	0.553*** (0.079)	0.520*** (0.080)
discovery:GSD_rl_pe	-1.397*** (0.433)	-1.326*** (0.412)	-0.899** (0.406)	-0.489 (0.391)	0.099 (0.393)

--					
Observations	454	439	424	409	394
R2	0.117	0.145	0.121	0.147	0.142
Adjusted R2	0.012	0.042	0.014	0.041	0.034
F Statistic	13.357*** (df = 4; 405)	16.595*** (df = 4; 391)	12.975*** (df = 4; 377)	15.661*** (df = 4; 363)	14.434*** (df = 4; 349)
=====					
--					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9, + type = "text")					
=====					
--					
Dependent variable:					
--					
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)

--					
discovery	0.099 (0.163)	0.049 (0.163)	-0.016 (0.162)	-0.159 (0.163)	-0.102 (0.164)
GSD_rl_pe	-0.460** (0.182)	-0.389** (0.189)	-0.187 (0.197)	-0.229 (0.204)	-0.363* (0.217)
pre_dis10	0.556*** (0.080)	0.579*** (0.081)	0.602*** (0.082)	0.564*** (0.081)	0.472*** (0.082)
discovery:GSD_rl_pe	0.579 (0.389)	0.680* (0.387)	0.677* (0.384)	1.040*** (0.382)	1.083*** (0.384)

--					
Observations	379	364	349	334	319
R2	0.176	0.187	0.184	0.194	0.180
Adjusted R2	0.071	0.081	0.075	0.084	0.065
F Statistic	17.937*** (df = 4; 335)	18.474*** (df = 4; 321)	17.306*** (df = 4; 307)	17.591*** (df = 4; 293)	15.320*** (df = 4; 279)
=====					
--					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4, + type = "text")					
=====					
--					
Dependent variable:					
--					
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)

--					
discovery	0.454** (0.206)	0.421** (0.196)	0.637*** (0.190)	0.542*** (0.183)	0.779*** (0.182)
VD_rl	0.011 (0.152)	0.059 (0.148)	0.093 (0.148)	0.128 (0.146)	0.198 (0.147)

pre_dis10	0.476*** (0.090)	0.586*** (0.086)	0.586*** (0.084)	0.632*** (0.082)	0.635*** (0.082)					
discovery:VD_r1	-3.878*** (1.139)	-3.295*** (1.083)	-3.877*** (1.050)	-3.082*** (1.013)	-3.577*** (1.009)					
<hr/>										
Observations	454	439	424	409	394					
R2	0.087	0.119	0.122	0.145	0.157					
Adjusted R2	-0.021	0.013	0.015	0.039	0.050					
F Statistic	9.631*** (df = 4; 405)	13.208*** (df = 4; 391)	13.123*** (df = 4; 377)	15.409*** (df = 4; 363)	16.213*** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
<hr/>										
discovery	0.953*** (0.178)	0.685*** (0.179)	0.389** (0.178)	0.373** (0.176)	0.653*** (0.174)					
VD_r1	0.283* (0.146)	0.336** (0.150)	0.401*** (0.153)	0.473*** (0.155)	0.538*** (0.159)					
pre_dis10	0.698*** (0.081)	0.685*** (0.082)	0.661*** (0.083)	0.637*** (0.082)	0.589*** (0.082)					
discovery:VD_r1	-4.020*** (0.988)	-2.424** (0.994)	-0.976 (0.987)	-0.905 (0.976)	-2.190** (0.973)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.205	0.198	0.195	0.199	0.198					
Adjusted R2	0.103	0.093	0.087	0.090	0.086					
F Statistic	21.573*** (df = 4; 335)	19.771*** (df = 4; 321)	18.564*** (df = 4; 307)	18.212*** (df = 4; 293)	17.255*** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)					
<hr/>										
discovery	1.971* (1.065)	2.034* (1.049)	1.410 (1.050)	0.708 (1.052)	-0.246 (1.044)					
EFW	-0.037 (0.052)	0.036 (0.053)	0.066 (0.055)	0.098* (0.057)	0.137** (0.058)					
pre_dis10	0.276** (0.111)	0.381*** (0.113)	0.276** (0.118)	0.282** (0.124)	0.175 (0.132)					
discovery:EFW	-0.442** (0.186)	-0.436** (0.183)	-0.315* (0.184)	-0.167 (0.184)	0.026 (0.182)					
<hr/>										
Observations	282	269	256	243	230					
R2	0.170	0.163	0.123	0.082	0.049					
Adjusted R2	0.041	0.029	-0.021	-0.074	-0.116					
F Statistic	12.484*** (df = 4; 243)	11.256*** (df = 4; 231)	7.664*** (df = 4; 219)	4.599*** (df = 4; 207)	2.527** (df = 4; 195)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")										
<hr/>										
Dependent variable:										
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)					
<hr/>										
discovery	-1.554 (1.048)	-1.482 (1.043)	-2.648** (1.083)	-2.448** (1.155)	-3.052*** (1.147)					
EFW	0.072 (0.059)	0.040 (0.060)	0.019 (0.063)	0.018 (0.064)	-0.003 (0.067)					

pre_dis10	0.232 (0.145)	0.212 (0.165)	0.017 (0.213)	-0.038 (0.211)	0.016 (0.208)
discovery:IEF	0.272 (0.183)	0.275 (0.182)	0.483** (0.190)	0.450** (0.204)	0.565*** (0.202)

=====
Observations 217 204 191 178 165
R2 0.040 0.030 0.048 0.041 0.069
Adjusted R2 -0.133 -0.151 -0.138 -0.155 -0.132
F Statistic 1.928 (df = 4; 183) 1.324 (df = 4; 171) 1.985* (df = 4; 159) 1.570 (df = 4; 147) 2.484** (df = 4; 135)
=====
Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4,
+ type = "text")

Dependent variable:					
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)
discovery	2.546** (1.104)	2.350** (1.087)	3.056*** (1.089)	1.571 (1.077)	1.101 (1.044)
IEF	0.002 (0.004)	0.003 (0.004)	0.001 (0.005)	0.001 (0.005)	0.00005 (0.005)
pre_dis10	0.213** (0.106)	0.341*** (0.107)	0.225** (0.110)	0.270** (0.112)	0.191* (0.112)
discovery:IEF	-0.055** (0.022)	-0.050** (0.021)	-0.062*** (0.021)	-0.032 (0.021)	-0.021 (0.021)

=====
Observations 351 337 323 309 295
R2 0.062 0.069 0.047 0.033 0.014
Adjusted R2 -0.070 -0.064 -0.092 -0.112 -0.136
F Statistic 5.032*** (df = 4; 307) 5.445*** (df = 4; 294) 3.442*** (df = 4; 281) 2.255* (df = 4; 268) 0.936 (df = 4; 255)
=====
Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9,
+ type = "text")

Dependent variable:					
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)
discovery	0.840 (0.969)	0.606 (0.938)	-0.333 (0.946)	-0.875 (0.942)	-0.680 (0.941)
IEF	0.002 (0.004)	0.001 (0.004)	0.001 (0.004)	-0.001 (0.004)	-0.001 (0.005)
pre_dis10	0.225** (0.108)	0.199* (0.110)	0.085 (0.120)	-0.015 (0.119)	-0.071 (0.119)
discovery:IEF	-0.014 (0.019)	-0.008 (0.019)	0.009 (0.019)	0.018 (0.019)	0.015 (0.019)

=====
Observations 281 267 253 239 225
R2 0.025 0.026 0.013 0.006 0.013
Adjusted R2 -0.128 -0.131 -0.152 -0.165 -0.164
F Statistic 1.531 (df = 4; 242) 1.550 (df = 4; 229) 0.704 (df = 4; 216) 0.318 (df = 4; 203) 0.605 (df = 4; 190)
=====

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4,
+ type = "text")

Dependent variable:					
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)
discovery	-2.470*** (0.453)	-2.152*** (0.444)	-1.844*** (0.451)	-1.435*** (0.444)	-1.082** (0.444)
CBIE	-0.801***	-0.618***	-0.521**	-0.432*	-0.453**

	(0.213)	(0.214)	(0.223)	(0.224)	(0.230)
pre_dis10	0.402*** (0.099)	0.556*** (0.098)	0.548*** (0.101)	0.614*** (0.101)	0.563*** (0.102)
discovery:CBIE	4.032*** (0.800)	3.592*** (0.783)	3.262*** (0.795)	2.638*** (0.782)	2.263*** (0.781)
Observations	362	349	336	323	310
R2	0.129	0.142	0.117	0.128	0.112
Adjusted R2	0.002	0.015	-0.016	-0.007	-0.028
F Statistic	11.710*** (df = 4; 315)	12.554*** (df = 4; 303)	9.656*** (df = 4; 291)	10.206*** (df = 4; 279)	8.416*** (df = 4; 267)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")					
Dependent variable:					
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)
discovery	-0.813* (0.433)	0.098 (0.428)	0.277 (0.413)	0.093 (0.410)	0.109 (0.398)
CBIE	-0.526** (0.230)	-0.657*** (0.235)	-0.898*** (0.236)	-1.028*** (0.243)	-0.993*** (0.246)
pre_dis10	0.553*** (0.102)	0.562*** (0.103)	0.615*** (0.102)	0.564*** (0.102)	0.328*** (0.100)
discovery:CBIE	1.929** (0.762)	0.279 (0.752)	-0.143 (0.727)	0.115 (0.720)	0.126 (0.699)
Observations	297	284	271	258	245
R2	0.123	0.143	0.186	0.178	0.126
Adjusted R2	-0.017	0.001	0.049	0.036	-0.030
F Statistic	8.981*** (df = 4; 255)	10.101*** (df = 4; 243)	13.196*** (df = 4; 231)	11.884*** (df = 4; 219)	7.449*** (df = 4; 207)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
Dependent variable:					
	TES_cap (1)	TES_cap1 (2)	TES_cap2 (3)	TES_cap3 (4)	TES_cap4 (5)
discovery	1.440** (0.562)	1.537*** (0.537)	1.314** (0.530)	0.283 (0.513)	-0.180 (0.515)
EcGI	-0.012*** (0.003)	-0.008*** (0.003)	-0.005* (0.003)	-0.003 (0.003)	-0.001 (0.003)
pre_dis10	0.429*** (0.085)	0.543*** (0.081)	0.518*** (0.081)	0.569*** (0.079)	0.545*** (0.080)
discovery:EcGI	-0.031*** (0.011)	-0.032*** (0.010)	-0.025** (0.010)	-0.005 (0.010)	0.008 (0.010)
Observations	454	439	424	409	394
R2	0.122	0.140	0.113	0.126	0.124
Adjusted R2	0.018	0.036	0.005	0.018	0.014
F Statistic	14.058*** (df = 4; 405)	15.857*** (df = 4; 391)	12.055*** (df = 4; 377)	13.096*** (df = 4; 363)	12.351*** (df = 4; 349)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	TES_cap5 (1)	TES_cap6 (2)	TES_cap7 (3)	TES_cap8 (4)	TES_cap9 (5)
discovery	-0.534 (0.506)	-0.903* (0.499)	-1.195** (0.491)	-1.230** (0.486)	-0.945* (0.488)

EcGI	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.005 (0.003)
pre_dis10	0.589*** (0.080)	0.612*** (0.079)	0.622*** (0.079)	0.598*** (0.079)	0.504*** (0.080)
discovery:EcGI	0.016* (0.010)	0.023** (0.010)	0.028*** (0.009)	0.028*** (0.009)	0.024** (0.009)
<hr/>					
Observations	379	364	349	334	319
R2	0.165	0.187	0.198	0.198	0.180
Adjusted R2	0.058	0.080	0.091	0.089	0.066
F Statistic	16.539*** (df = 4; 335)	18.401*** (df = 4; 321)	18.969*** (df = 4; 307)	18.102*** (df = 4; 293)	15.340*** (df = 4; 279)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				

2. Energy mix

2.1. Fossil energy (FE)

Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-2,585.274*** (626.261)	-2,541.484*** (620.237)	-2,356.733*** (637.647)	-1,511.271** (635.854)	-733.627 (639.216)
WGI	-23.425 (33.036)	-1.993 (34.051)	1.901 (35.742)	7.385 (36.209)	5.177 (37.116)
pre_dis10	-57.102 (179.830)	26.855 (191.701)	104.874 (217.127)	176.636 (220.396)	185.895 (226.203)
discovery:WGI	-289.412** (115.792)	-275.415** (114.842)	-269.329** (118.391)	-190.993 (117.956)	-90.028 (118.470)
<hr/>					
Observations	360	348	333	318	303
R2	0.114	0.122	0.098	0.039	0.013
Adjusted R2	0.0001	0.004	-0.025	-0.096	-0.129
F Statistic	10.262*** (df = 4; 318)	10.628*** (df = 4; 306)	7.941*** (df = 4; 292)	2.809** (df = 4; 278)	0.873 (df = 4; 264)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					
<hr/>					

Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,371.991** (621.787)	-628.418 (626.179)	-224.529 (622.290)	92.812 (582.381)	-707.808 (618.713)
WGI	-3.766 (37.022)	-14.875 (38.353)	-25.054 (39.567)	-17.522 (38.448)	-37.177 (42.526)
pre_dis10	216.007 (225.548)	219.514 (234.083)	257.948 (241.488)	135.519 (237.189)	-39.762 (266.604)
discovery:WGI	-176.521 (115.118)	-80.668 (115.799)	-45.558 (114.950)	21.819 (107.438)	-61.153 (113.356)
<hr/>					
Observations	288	273	258	243	228
R2	0.038	0.013	0.007	0.003	0.026
Adjusted R2	-0.105	-0.138	-0.149	-0.160	-0.139
F Statistic	2.459** (df = 4; 250)	0.777 (df = 4; 236)	0.406 (df = 4; 222)	0.175 (df = 4; 208)	1.311 (df = 4; 194)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")					
<hr/>					

Dependent variable:				
	FE	FE1	FE2	FE3
				FE4

	(1)	(2)	(3)	(4)	(5)					
discovery	-126.631 (939.389)	626.456 (957.170)	594.813 (977.010)	-334.941 (1,092.147)	-456.424 (1,146.103)					
SFI	57.710*** (20.033)	55.627*** (20.412)	52.046** (20.835)	45.472* (23.298)	49.337** (24.441)					
pre_dis10	74.418 (174.208)	207.472 (177.506)	219.973 (181.185)	234.607 (202.537)	246.670 (212.543)					
discovery:SFI	-18.504 (62.248)	-69.583 (63.426)	-60.335 (64.741)	21.903 (72.371)	35.177 (75.946)					
Observations	360	360	360	360	360					
R2	0.051	0.055	0.040	0.020	0.021					
Adjusted R2	-0.071	-0.067	-0.084	-0.107	-0.105					
F Statistic (df = 4; 318)	4.282***	4.603***	3.301**	1.602	1.730					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model5.5,model5.6,model5.7,model5.8,model5.9,										
+ type = "text")										
=====										
Dependent variable:										
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)					
discovery	-273.762 (1,117.953)	543.137 (1,098.737)	-353.027 (1,072.158)	207.470 (1,034.278)	249.367 (1,030.299)					
SFI	55.000** (24.633)	53.219** (25.475)	54.268** (25.879)	66.019** (26.095)	66.235** (27.401)					
pre_dis10	265.129 (210.988)	397.597* (211.514)	345.936 (211.293)	353.273* (209.564)	139.114 (215.577)					
discovery:SFI	14.767 (74.040)	-25.873 (72.718)	43.637 (70.895)	8.951 (68.313)	-20.980 (68.129)					
Observations	348	333	318	303	288					
R2	0.026	0.028	0.037	0.045	0.025					
Adjusted R2	-0.105	-0.105	-0.098	-0.092	-0.119					
F Statistic	2.010* (df = 4; 306)	2.085* (df = 4; 292)	2.695** (df = 4; 278)	3.119** (df = 4; 264)	1.626 (df = 4; 250)					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model6.0,model6.1,model6.2,model6.3,model6.4,										
+ type = "text")										
=====										
Dependent variable:										
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)					
discovery	-28.665 (367.863)	-333.049 (322.605)	-315.389 (302.644)	-219.003 (293.930)	-38.218 (296.194)					
CSCI	27.843 (63.403)	25.164 (56.313)	19.837 (53.438)	2.679 (52.453)	1.660 (53.537)					
pre_dis10	60.085 (206.916)	169.673 (189.138)	272.506 (186.574)	356.393* (182.131)	384.335** (184.599)					
discovery:CSCI	357.432 (352.297)	39.741 (310.434)	-99.951 (293.183)	-268.387 (284.365)	-258.037 (286.177)					
Observations	469	454	439	424	409					
R2	0.009	0.013	0.011	0.011	0.013					
Adjusted R2	-0.109	-0.107	-0.110	-0.113	-0.112					
F Statistic	0.982 (df = 4; 418)	1.283 (df = 4; 404)	1.111 (df = 4; 390)	1.002 (df = 4; 376)	1.209 (df = 4; 362)					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model6.5,model6.6,model6.7,model6.8,model6.9,										
+ type = "text")										
=====										
Dependent variable:										

	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-243.678 (296.701)	-105.225 (298.325)	-4.129 (294.880)	230.830 (287.767)	-342.339 (287.237)
CSCI	3.041 (54.356)	-13.464 (55.686)	-20.374 (56.131)	-20.090 (56.063)	-16.609 (57.088)
pre_dis10	447.767** (186.128)	496.837*** (188.503)	521.840*** (187.834)	494.273*** (185.009)	455.640** (185.243)
discovery:CSCI	-410.445 (286.252)	-404.970 (287.365)	-401.139 (283.565)	-222.794 (276.227)	-496.314* (272.807)

Observations	394	379	364	349	334
R2	0.018	0.024	0.031	0.036	0.025
Adjusted R2	-0.109	-0.104	-0.099	-0.097	-0.112
F Statistic	1.565 (df = 4; 348)	2.070* (df = 4; 334)	2.597** (df = 4; 320)	2.822** (df = 4; 306)	1.898 (df = 4; 292)

Note:
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4,
+ type = "text")

Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	630.584 (878.531)	717.636 (770.636)	827.094 (725.680)	613.264 (704.009)	389.141 (707.996)
GSD_rl	-231.025 (762.155)	-333.550 (685.019)	-501.514 (660.727)	-659.188 (657.768)	-618.483 (674.050)
pre_dis10	183.741 (202.174)	257.723 (183.584)	342.544* (179.882)	358.037** (175.621)	354.976** (177.849)
discovery:GSD_rl	-3,072.852 (2,755.893)	-3,483.309 (2,415.651)	-3,402.059 (2,272.385)	-1,959.735 (2,205.465)	-675.803 (2,218.907)

Observations	483	468	453	438	423
R2	0.009	0.018	0.018	0.013	0.014
Adjusted R2	-0.105	-0.098	-0.099	-0.106	-0.107
F Statistic	1.023 (df = 4; 432)	1.874 (df = 4; 418)	1.851 (df = 4; 404)	1.319 (df = 4; 390)	1.338 (df = 4; 376)

Note:
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9,
+ type = "text")

Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	616.946 (708.032)	338.249 (710.002)	307.116 (699.216)	-4.382 (677.201)	500.553 (670.164)
GSD_rl	-497.946 (685.777)	-469.764 (700.273)	-430.158 (706.222)	-455.873 (700.465)	-360.492 (709.215)
pre_dis10	407.569** (179.224)	425.991** (181.260)	440.850** (180.210)	418.944** (176.412)	385.840** (176.840)
discovery:GSD_rl	-1,677.665 (2,220.038)	-347.365 (2,227.352)	64.589 (2,194.796)	1,367.552 (2,127.061)	-1,396.766 (2,109.521)

Observations	408	393	378	363	348
R2	0.016	0.020	0.026	0.036	0.016
Adjusted R2	-0.107	-0.104	-0.099	-0.090	-0.116
F Statistic	1.429 (df = 4; 362)	1.774 (df = 4; 348)	2.253* (df = 4; 334)	2.991** (df = 4; 320)	1.258 (df = 4; 306)

Note:
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4,
+ type = "text")

Dependent variable:

	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)					
discovery	146.890 (390.653)	18.771 (320.423)	47.131 (286.522)	72.279 (300.483)	273.551 (325.978)					
PLTV_xconst	62.174 (47.993)	68.911* (39.365)	54.736 (35.200)	46.644 (36.915)	46.049 (40.047)					
pre_dis10	283.642 (202.170)	293.394* (165.825)	299.919** (148.280)	329.699** (155.595)	342.451** (168.700)					
discovery:PLTV_xconst	-76.499 (125.739)	-54.011 (103.134)	-26.537 (92.222)	13.024 (96.716)	-37.687 (104.922)					
Observations	420	420	420	420	420					
R2	0.010	0.018	0.017	0.016	0.015					
Adjusted R2	-0.109	-0.100	-0.101	-0.102	-0.103					
F Statistic (df = 4; 374)	0.964	1.739	1.618	1.536	1.433					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")										
<hr/>										
Dependent variable:										
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)					
discovery	456.875 (325.373)	223.924 (327.585)	256.952 (323.385)	141.123 (313.814)	471.410 (310.710)					
PLTV_xconst	40.062 (40.458)	24.298 (41.176)	14.849 (41.153)	3.683 (40.492)	6.468 (40.801)					
pre_dis10	376.887** (169.584)	418.059** (172.090)	440.669** (171.376)	443.602*** (167.937)	365.130** (168.390)					
discovery:PLTV_xconst	-138.749 (104.942)	2.124 (105.895)	26.785 (104.796)	106.863 (101.970)	-157.706 (101.604)					
Observations	408	393	378	363	348					
R2	0.019	0.020	0.026	0.037	0.022					
Adjusted R2	-0.103	-0.104	-0.100	-0.089	-0.110					
F Statistic	1.745 (df = 4; 362)	1.742 (df = 4; 348)	2.217* (df = 4; 334)	3.084** (df = 4; 320)	1.686 (df = 4; 306)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4, + type = "text")										
<hr/>										
Dependent variable:										
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)					
discovery	-1,807.514*** (395.460)	-2,041.636*** (389.033)	-1,786.296*** (400.103)	-883.877** (401.616)	-151.299 (404.650)					
WGI_ge	-55.805 (150.927)	87.530 (152.574)	129.011 (160.470)	141.650 (163.084)	146.351 (168.056)					
pre_dis10	-109.092 (179.964)	4.043 (189.860)	70.988 (213.744)	133.866 (217.490)	139.990 (222.672)					
discovery:WGI_ge	-918.736** (455.086)	-1,207.866*** (447.704)	-1,077.021** (460.818)	-477.660 (461.409)	139.920 (463.754)					
Observations	360	348	333	318	303					
R2	0.108	0.126	0.100	0.035	0.014					
Adjusted R2	-0.007	0.009	-0.024	-0.100	-0.127					
F Statistic	9.586*** (df = 4; 318)	11.049*** (df = 4; 306)	8.072*** (df = 4; 292)	2.540** (df = 4; 278)	0.968 (df = 4; 264)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9, + type = "text")										
<hr/>										

Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,003.352** (395.725)	-539.088 (400.833)	350.365 (400.664)	349.983 (377.054)	-956.239** (432.888)
WGI_ge	125.451 (166.463)	88.607 (171.406)	39.402 (175.610)	13.588 (171.503)	13.388 (188.924)
pre_dis10	191.923 (222.147)	213.828 (230.669)	189.934 (238.135)	93.838 (233.924)	-18.522 (263.327)
discovery:WGI_ge	-710.022 (452.248)	-427.898 (456.470)	433.832 (454.426)	472.106 (425.500)	-700.306 (477.683)
Observations	288	273	258	243	228
R2	0.039	0.014	0.009	0.008	0.031
Adjusted R2	-0.103	-0.136	-0.147	-0.154	-0.134
F Statistic	2.537** (df = 4; 250)	0.857 (df = 4; 236)	0.520 (df = 4; 222)	0.443 (df = 4; 208)	1.565 (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4, + type = "text")					
Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-2,515.974*** (846.972)	-2,701.204*** (836.142)	-2,216.406** (858.220)	-1,237.104 (854.718)	21.739 (856.653)
WGI_rl	-194.913 (175.046)	-71.394 (178.407)	-58.007 (186.168)	-53.810 (188.339)	-128.172 (191.292)
pre_dis10	-118.763 (178.687)	-31.880 (189.629)	24.446 (214.087)	113.611 (216.963)	130.638 (222.025)
discovery:WGI_rl	-1,281.795* (751.729)	-1,431.626* (742.097)	-1,127.947 (762.096)	-640.028 (758.344)	275.592 (759.393)
Observations	360	348	333	318	303
R2	0.107	0.117	0.089	0.033	0.013
Adjusted R2	-0.008	-0.002	-0.035	-0.103	-0.129
F Statistic	9.512*** (df = 4; 318)	10.107*** (df = 4; 306)	7.160*** (df = 4; 292)	2.340* (df = 4; 278)	0.868 (df = 4; 264)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9, + type = "text")					
Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,455.044* (833.513)	-596.376 (839.757)	1,200.628 (831.612)	1,162.481 (778.111)	-1,242.340 (887.948)
WGI_rl	-178.708 (189.655)	-131.814 (196.228)	-101.904 (201.935)	-48.096 (194.797)	-113.767 (211.904)
pre_dis10	165.724 (221.441)	192.809 (229.929)	181.093 (236.446)	88.331 (232.282)	-39.900 (262.597)
discovery:WGI_rl	-887.429 (738.167)	-338.181 (742.921)	1,087.709 (734.922)	1,074.932 (686.826)	-752.896 (773.532)
Observations	288	273	258	243	228
R2	0.038	0.013	0.015	0.014	0.027
Adjusted R2	-0.105	-0.138	-0.140	-0.147	-0.139
F Statistic	2.458** (df = 4; 250)	0.773 (df = 4; 236)	0.856 (df = 4; 222)	0.742 (df = 4; 208)	1.335 (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4, + type = "text")					

Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-1,492.807*** (261.870)	-1,530.482*** (261.370)	-1,376.180*** (267.938)	-760.262*** (268.416)	-423.079 (269.683)
WGI_rq	-452.581*** (132.501)	-306.654** (140.340)	-317.281** (149.849)	-317.343** (153.336)	-350.809** (158.218)
pre_dis10	-113.050 (175.401)	-22.866 (188.418)	44.281 (212.753)	119.501 (216.342)	158.251 (221.282)
discovery:WGI_rq	-646.214** (274.823)	-633.407** (274.681)	-623.909** (282.351)	-360.177 (282.039)	-237.827 (282.478)
Observations	360	348	333	318	303
R2	0.146	0.137	0.114	0.052	0.033
Adjusted R2	0.036	0.022	-0.007	-0.081	-0.106
F Statistic	13.618*** (df = 4; 318)	12.171*** (df = 4; 306)	9.416*** (df = 4; 292)	3.843*** (df = 4; 278)	2.287* (df = 4; 264)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9, + type = "text")					
Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-786.276*** (264.115)	-331.795 (268.096)	-34.671 (268.593)	-61.552 (253.125)	-583.131** (270.318)
WGI_rq	-229.150 (159.391)	-196.105 (165.986)	-114.909 (169.576)	-35.037 (164.432)	-64.186 (179.899)
pre_dis10	191.529 (221.421)	201.139 (230.591)	239.424 (238.607)	152.562 (234.360)	-35.829 (263.617)
discovery:WGI_rq	-481.743* (275.612)	-175.224 (278.420)	-65.426 (277.469)	-62.339 (259.703)	-281.400 (272.841)
Observations	288	273	258	243	228
R2	0.051	0.018	0.007	0.003	0.027
Adjusted R2	-0.090	-0.131	-0.149	-0.160	-0.138
F Statistic	3.342** (df = 4; 250)	1.110 (df = 4; 236)	0.394 (df = 4; 222)	0.147 (df = 4; 208)	1.351 (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4, + type = "text")					
Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-770.002* (444.398)	-674.703* (388.833)	-442.806 (364.631)	168.267 (354.711)	374.330 (357.479)
GSD_rl_pe	-540.851 (410.442)	-470.026 (365.367)	-306.137 (349.947)	-170.179 (348.873)	-142.366 (361.286)
pre_dis10	78.026 (195.912)	142.413 (177.046)	225.781 (172.430)	311.711* (168.461)	345.129** (170.650)
discovery:GSD_rl_pe	1,286.587 (1,070.095)	896.321 (934.083)	603.406 (873.483)	-448.871 (848.350)	-537.211 (853.665)
Observations	483	468	453	438	423
R2	0.013	0.017	0.014	0.010	0.013
Adjusted R2	-0.102	-0.098	-0.104	-0.109	-0.108
F Statistic	1.380 (df = 4; 432)	1.845 (df = 4; 418)	1.387 (df = 4; 404)	0.997 (df = 4; 390)	1.255 (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9, + type = "text")					

Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-38.953 (359.068)	408.486 (361.108)	538.356 (357.018)	766.566** (347.145)	-187.372 (350.502)
GSD_rl_pe	-146.283 (373.814)	-94.249 (388.005)	-58.567 (396.685)	-36.068 (401.466)	-176.790 (418.519)
pre_dis10	344.281** (172.471)	424.251** (174.753)	453.538*** (174.336)	475.837*** (171.494)	316.790* (173.785)
discovery:GSD_rl_pe	376.378 (856.066)	-485.529 (859.393)	-576.577 (847.995)	-951.008 (822.664)	696.644 (820.119)
Observations	408	393	378	363	348
R2	0.013	0.020	0.027	0.038	0.016
Adjusted R2	-0.109	-0.104	-0.099	-0.088	-0.115
F Statistic	1.214 (df = 4; 362)	1.759 (df = 4; 348)	2.292* (df = 4; 334)	3.146** (df = 4; 320)	1.279 (df = 4; 306)
Note: *p<0.1; **p<0.05; ***p<0.01					
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4, + type = "text")					
Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-168.972 (494.417)	12.662 (433.159)	209.483 (407.387)	331.093 (395.312)	454.110 (397.992)
VD_rl	-511.286 (351.959)	-525.540* (312.928)	-531.011* (299.700)	-504.255* (298.641)	-409.559 (309.654)
pre_dis10	141.801 (200.372)	226.421 (181.674)	314.270* (177.810)	350.216** (173.658)	373.948** (176.078)
discovery:VD_rl	-848.755 (2,736.765)	-2,238.685 (2,397.016)	-2,650.517 (2,252.943)	-1,988.688 (2,188.332)	-1,695.481 (2,205.526)
Observations	483	468	453	438	423
R2	0.011	0.021	0.022	0.018	0.018
Adjusted R2	-0.103	-0.094	-0.094	-0.100	-0.102
F Statistic	1.238 (df = 4; 432)	2.222* (df = 4; 418)	2.280* (df = 4; 404)	1.790 (df = 4; 390)	1.698 (df = 4; 376)
Note: *p<0.1; **p<0.05; ***p<0.01					
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text")					
Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	590.419 (398.046)	499.955 (400.036)	619.973 (394.260)	464.120 (382.962)	606.338 (378.567)
VD_rl	-316.639 (317.756)	-253.707 (323.873)	-204.500 (324.462)	-157.312 (321.036)	-91.393 (324.861)
pre_dis10	434.279** (177.482)	454.654** (179.919)	484.597*** (179.035)	459.410*** (175.787)	431.132** (175.772)
discovery:VD_rl	-3,051.282 (2,208.377)	-1,676.803 (2,222.227)	-1,829.640 (2,193.198)	-301.766 (2,133.599)	-3,343.854 (2,102.424)
Observations	408	393	378	363	348
R2	0.020	0.022	0.028	0.034	0.022
Adjusted R2	-0.101	-0.102	-0.097	-0.092	-0.109
F Statistic	1.888 (df = 4; 362)	1.958 (df = 4; 348)	2.444** (df = 4; 334)	2.851** (df = 4; 320)	1.740 (df = 4; 306)
Note: *p<0.1; **p<0.05; ***p<0.01					
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4,					

```
+     type = "text")
```

Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-10,985.380*** (2,425.450)	-9,069.536*** (2,369.881)	-10,126.030*** (2,421.406)	-8,944.108*** (2,524.321)	-9,748.412*** (2,457.416)
EFW	114.834 (110.846)	92.377 (112.790)	21.906 (118.473)	54.566 (129.175)	96.994 (129.502)
pre_dis10	-217.720 (217.138)	-164.226 (226.467)	-234.109 (251.878)	-162.751 (271.428)	-196.111 (275.196)
discovery:EFW	1,696.869*** (424.623)	1,352.723*** (414.691)	1,558.880*** (423.455)	1,444.348*** (441.237)	1,630.755*** (429.323)
Observations	304	294	281	268	255
R2	0.192	0.194	0.177	0.091	0.088
Adjusted R2	0.073	0.070	0.048	-0.055	-0.062
F Statistic	15.684*** (df = 4; 264)	15.274*** (df = 4; 254)	13.053*** (df = 4; 242)	5.786*** (df = 4; 230)	5.287*** (df = 4; 218)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9,					
+ type = "text")					

Dependent variable:					
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-11,230.960*** (2,322.844)	-6,160.114** (2,395.240)	-13,844.340*** (2,266.481)	-8,367.972*** (2,322.809)	-9,275.850*** (2,513.549)
EFW	70.975 (125.584)	64.857 (133.273)	-53.015 (127.911)	13.445 (133.597)	-45.126 (136.105)
pre_dis10	-237.876 (273.824)	-91.032 (301.820)	-169.893 (312.806)	-70.035 (365.919)	-578.264 (462.497)
discovery:EFW	1,851.881*** (405.605)	1,014.718** (418.032)	2,406.975*** (395.287)	1,464.993*** (404.845)	1,529.465*** (443.538)
Observations	242	229	216	203	190
R2	0.142	0.049	0.171	0.074	0.111
Adjusted R2	-0.004	-0.118	0.021	-0.101	-0.063
F Statistic	8.524*** (df = 4; 206)	2.502** (df = 4; 194)	9.395*** (df = 4; 182)	3.373** (df = 4; 170)	4.932*** (df = 4; 158)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4,					
+ type = "text")					

Dependent variable:					
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	916.729 (2,360.022)	566.812 (2,362.742)	1,107.267 (2,382.807)	394.156 (2,379.059)	-458.857 (2,312.357)
IEF	-7.309 (9.183)	-9.242 (9.284)	-14.066 (9.532)	-15.111 (9.775)	-15.610 (9.672)
pre_dis10	-142.344 (194.614)	-72.401 (208.625)	-15.220 (229.221)	77.728 (233.715)	117.271 (232.874)
discovery:IEF	-33.808 (46.616)	-26.583 (46.660)	-34.865 (47.039)	-12.425 (46.964)	8.151 (45.648)
Observations	378	364	350	336	322
R2	0.048	0.048	0.040	0.013	0.011
Adjusted R2	-0.081	-0.083	-0.095	-0.129	-0.134
F Statistic	4.205*** (df = 4; 332)	4.025*** (df = 4; 319)	3.184** (df = 4; 306)	0.960 (df = 4; 293)	0.757 (df = 4; 280)
Note:	*p<0.1; **p<0.05; ***p<0.01				

```

> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9,
+             type = "text")
=====
                                         Dependent variable:
-----
```

	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-40.877 (2,255.532)	-434.645 (2,213.363)	-2,877.661 (2,165.631)	-1,711.226 (2,102.070)	394.477 (2,078.731)
IEF	-18.171* (9.602)	-20.686** (9.660)	-17.870* (9.637)	-19.367** (9.563)	-23.737** (9.629)
pre_dis10	108.302 (233.694)	184.678 (237.277)	206.216 (242.079)	188.287 (247.605)	-74.803 (262.769)
discovery:IEF	-2.925 (44.526)	9.284 (43.694)	61.157 (42.751)	38.824 (41.495)	-11.697 (41.096)

=====
Observations 308 294 280 266 252
R2 0.017 0.021 0.030 0.031 0.031
Adjusted R2 -0.130 -0.130 -0.123 -0.126 -0.131
F Statistic 1.185 (df = 4; 267) 1.342 (df = 4; 254) 1.841 (df = 4; 241) 1.844 (df = 4; 228) 1.723 (df = 4; 215)
=====

Note: *p<0.1; **p<0.05; ***p<0.01

```

> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4,
+             type = "text")
=====
```

```

                                         Dependent variable:
-----
```

	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	-2,976.786*** (1,096.017)	-2,938.719*** (1,027.418)	-2,717.324*** (1,006.488)	-2,354.927** (1,014.630)	-1,962.456* (1,013.150)
CBIE	-1,643.482*** (504.989)	-1,809.914*** (478.525)	-1,952.738*** (474.505)	-1,902.239*** (489.519)	-1,937.044*** (501.348)
pre_dis10	141.859 (214.238)	231.283 (210.925)	321.064 (219.592)	444.703** (223.795)	513.040** (226.110)
discovery:CBIE	3,885.069** (1,928.847)	4,019.486** (1,809.971)	4,011.577** (1,775.841)	4,167.581** (1,789.266)	3,858.920** (1,785.403)

=====
Observations 387 374 361 348 335
R2 0.069 0.077 0.072 0.057 0.062
Adjusted R2 -0.063 -0.056 -0.064 -0.084 -0.080
F Statistic 6.301*** (df = 4; 338) 6.792*** (df = 4; 326) 6.122*** (df = 4; 314) 4.557*** (df = 4; 302) 4.832*** (df = 4; 290)
=====

Note: *p<0.1; **p<0.05; ***p<0.01

```

> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9,
+             type = "text")
=====
```

```

                                         Dependent variable:
-----
```

	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,958.538* (1,009.611)	-1,307.266 (987.465)	-1,112.415 (947.034)	-936.063 (922.021)	-1,390.187 (911.581)
CBIE	-2,113.363*** (510.429)	-2,199.358*** (511.716)	-2,339.561*** (504.252)	-2,435.972*** (506.975)	-2,777.216*** (520.333)
pre_dis10	538.058** (228.596)	624.324*** (227.323)	682.843*** (222.273)	691.963*** (221.399)	535.017** (225.828)
discovery:CBIE	3,692.114** (1,778.340)	2,895.480* (1,738.437)	2,786.509* (1,666.378)	2,552.750 (1,621.398)	2,664.980* (1,603.826)

=====
Observations 322 309 296 283 270
R2 0.070 0.087 0.112 0.127 0.117
Adjusted R2 -0.074 -0.057 -0.031 -0.017 -0.032
F Statistic 5.201*** (df = 4; 278) 6.318*** (df = 4; 266) 8.042*** (df = 4; 254) 8.789*** (df = 4; 242) 7.645*** (df = 4; 230)
=====

Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
<hr/>					
	Dependent variable:				
	FE (1)	FE1 (2)	FE2 (3)	FE3 (4)	FE4 (5)
discovery	9,757.753*** (1,281.673)	5,809.032*** (1,157.250)	4,239.293*** (1,094.391)	288.868 (1,080.603)	-901.407 (1,083.289)
EcGI	-27.723*** (6.181)	-22.926*** (5.704)	-20.943*** (5.509)	-22.861*** (5.579)	-24.298*** (5.751)
pre_dis10	317.675* (179.124)	306.819* (167.190)	347.377** (164.440)	365.113** (163.580)	393.825** (165.377)
discovery:EcGI	-196.242*** (24.858)	-119.957*** (22.436)	-86.773*** (21.206)	-4.716 (20.933)	22.048 (20.979)
Observations	480	468	453	438	423
R2	0.174	0.114	0.087	0.050	0.058
Adjusted R2	0.080	0.010	-0.021	-0.064	-0.058
F Statistic	22.610*** (df = 4; 430)	13.402*** (df = 4; 418)	9.624*** (df = 4; 404)	5.152*** (df = 4; 390)	5.740*** (df = 4; 376)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
<hr/>					
	Dependent variable:				
	FE5 (1)	FE6 (2)	FE7 (3)	FE8 (4)	FE9 (5)
discovery	-1,967.092* (1,084.950)	-3,405.810*** (1,074.754)	-3,892.354*** (1,049.880)	-3,421.504*** (1,020.910)	-3,921.605*** (1,008.167)
EcGI	-22.475*** (5.933)	-23.736*** (6.072)	-24.952*** (6.211)	-24.362*** (6.324)	-23.943*** (6.549)
pre_dis10	410.931** (167.103)	459.740*** (167.159)	490.246*** (165.092)	504.211*** (162.405)	401.295** (162.899)
discovery:EcGI	41.218* (21.004)	71.975*** (20.799)	83.376*** (20.310)	75.815*** (19.741)	78.857*** (19.483)
Observations	408	393	378	363	348
R2	0.057	0.085	0.106	0.109	0.094
Adjusted R2	-0.060	-0.031	-0.009	-0.008	-0.027
F Statistic	5.466*** (df = 4; 362)	8.054*** (df = 4; 348)	9.926*** (df = 4; 334)	9.793*** (df = 4; 320)	7.965*** (df = 4; 306)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				

2.2. Renewable energy (RE)

	<hr/>				
	Dependent variable:				
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-80.141** (34.058)	-119.709*** (33.157)	-56.527 (34.539)	-102.722*** (33.574)	-74.055** (33.975)
WGI	-7.473*** (1.797)	-5.762*** (1.820)	-5.587*** (1.936)	-5.818*** (1.912)	-6.729*** (1.973)
pre_dis10	12.159 (9.780)	6.128 (10.248)	-3.063 (11.761)	-4.054 (11.637)	-3.835 (12.023)
discovery:WGI	-10.614* (6.297)	-16.015*** (6.139)	-6.500 (6.413)	-11.231* (6.228)	-8.256 (6.297)
Observations	360	348	333	318	303
R2	0.085	0.097	0.048	0.107	0.082
Adjusted R2	-0.033	-0.024	-0.082	-0.019	-0.050

F Statistic	7.392*** (df = 4; 318)	8.184*** (df = 4; 306)	3.718*** (df = 4; 292)	8.310*** (df = 4; 278)	5.900*** (df = 4; 264)					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model4.5,model4.6,model4.7,model4.8,model4.9,										
+ type = "text")										
=====										
Dependent variable:										
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)					

discovery	-40.852 (35.885)	-55.384 (35.175)	-34.104 (36.890)	-62.070* (35.867)	-103.650*** (35.525)					
WGI	-7.446*** (2.137)	-8.098*** (2.154)	-7.872*** (2.346)	-6.468*** (2.368)	-5.144** (2.442)					
pre_dis10	-4.249 (13.017)	-3.038 (13.149)	-7.929 (14.316)	-14.698 (14.608)	-23.211 (15.308)					
discovery:WGI	-4.340 (6.644)	-6.251 (6.505)	-2.223 (6.814)	-5.161 (6.617)	-10.099 (6.509)					

Observations	288	273	258	243	228					
R2	0.060	0.080	0.066	0.082	0.128					
Adjusted R2	-0.079	-0.061	-0.082	-0.068	-0.020					
F Statistic	3.987*** (df = 4; 250)	5.106*** (df = 4; 236)	3.892*** (df = 4; 222)	4.625*** (df = 4; 208)	7.124*** (df = 4; 194)					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model5.0,model5.1,model5.2,model5.3,model5.4,										
+ type = "text")										
=====										
Dependent variable:										
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)					

discovery	-23.662 (32.573)	-23.775 (37.630)	-11.849 (46.142)	12.175 (54.198)	18.604 (56.775)					
SFI	-4.082*** (0.695)	-4.902*** (0.802)	-6.337*** (0.984)	-6.760*** (1.156)	-6.827*** (1.211)					
pre_dis10	-3.043 (6.041)	-4.375 (6.979)	-1.589 (8.557)	-4.798 (10.051)	-3.333 (10.529)					
discovery:SFI	1.525 (2.158)	1.208 (2.494)	0.918 (3.058)	-2.262 (3.591)	-2.216 (3.762)					

Observations	360	360	360	360	360					
R2	0.099	0.109	0.117	0.119	0.103					
Adjusted R2	-0.017	-0.006	0.003	0.006	-0.013					
F Statistic (df = 4; 318)	8.739***	9.723***	10.500***	10.781***	9.141***					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model5.5,model5.6,model5.7,model5.8,model5.9,										
+ type = "text")										
=====										
Dependent variable:										
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)					

discovery	-28.129 (58.128)	-47.663 (59.402)	-38.946 (61.109)	-55.480 (61.922)	-20.331 (60.279)					
SFI	-6.379*** (1.281)	-5.488*** (1.377)	-4.338*** (1.475)	-2.172 (1.562)	0.113 (1.603)					
pre_dis10	-6.997 (10.970)	-8.635 (11.435)	-10.243 (12.043)	-17.066 (12.546)	-19.419 (12.613)					
discovery:SFI	1.426 (3.850)	2.680 (3.931)	2.137 (4.041)	2.824 (4.090)	-0.404 (3.986)					

Observations	348	333	318	303	288					
R2	0.078	0.055	0.033	0.017	0.030					

Adjusted R2	-0.046	-0.075	-0.102	-0.124	-0.113
F Statistic	6.470*** (df = 4; 306)	4.216*** (df = 4; 292)	2.387* (df = 4; 278)	1.166 (df = 4; 264)	1.964 (df = 4; 250)
<hr/>					
Note:					
> stargazer(model6.0,model6.1,model6.2,model6.3,model6.4,					*p<0.1; **p<0.05; ***p<0.01
+ type = "text")					
<hr/>					
Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
<hr/>					
discovery	-23.411 (15.045)	-10.167 (15.156)	16.392 (14.854)	-27.180* (14.511)	-6.091 (14.819)
CSCI	-5.117** (2.593)	-4.598* (2.646)	-5.425** (2.623)	-4.648* (2.590)	-5.046* (2.679)
pre_dis10	6.320 (8.463)	-1.688 (8.885)	-10.298 (9.157)	-8.341 (8.992)	-10.192 (9.236)
discovery:CSCI	-11.402 (14.408)	1.259 (14.584)	17.481 (14.389)	-10.739 (14.039)	-0.911 (14.318)
<hr/>					
Observations	469	454	439	424	409
R2	0.019	0.012	0.014	0.025	0.014
Adjusted R2	-0.098	-0.108	-0.107	-0.097	-0.112
F Statistic	2.045* (df = 4; 418)	1.184 (df = 4; 404)	1.423 (df = 4; 390)	2.362* (df = 4; 376)	1.246 (df = 4; 362)
<hr/>					
Note:					
> stargazer(model6.5,model6.6,model6.7,model6.8,model6.9,					*p<0.1; **p<0.05; ***p<0.01
+ type = "text")					
<hr/>					
Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
<hr/>					
discovery	-20.375 (15.009)	-20.129 (15.069)	-25.102* (15.093)	-14.275 (15.051)	-29.527* (15.316)
CSCI	-5.231* (2.750)	-5.205* (2.813)	-4.642 (2.873)	-3.931 (2.932)	-2.838 (3.044)
pre_dis10	-7.428 (9.415)	-7.563 (9.521)	-7.744 (9.614)	-12.821 (9.676)	-15.538 (9.878)
discovery:CSCI	-16.560 (14.480)	-14.513 (14.515)	-17.663 (14.514)	-4.316 (14.447)	-8.540 (14.547)
<hr/>					
Observations	394	379	364	349	334
R2	0.020	0.020	0.021	0.016	0.030
Adjusted R2	-0.107	-0.110	-0.110	-0.119	-0.106
F Statistic	1.782 (df = 4; 348)	1.665 (df = 4; 334)	1.753 (df = 4; 320)	1.227 (df = 4; 306)	2.259* (df = 4; 292)
<hr/>					
Note:					
> stargazer(model7.0,model7.1,model7.2,model7.3,model7.4,					*p<0.1; **p<0.05; ***p<0.01
+ type = "text")					
<hr/>					
Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
<hr/>					
discovery	48.604 (35.509)	41.873 (35.802)	8.595 (35.386)	32.351 (34.371)	11.874 (35.038)
GSD_rl	-93.678*** (30.805)	-103.819*** (31.824)	-114.688*** (32.219)	-106.287*** (32.114)	-112.787*** (33.358)
pre_dis10	9.733 (8.172)	4.232 (8.529)	-3.466 (8.772)	-4.166 (8.574)	-6.496 (8.802)
discovery:GSD_rl	-203.336* (111.390)	-171.149 (112.224)	-19.843 (110.808)	-162.870 (107.676)	-54.342 (109.813)
<hr/>					
Observations	483	468	453	438	423

R2	0.037	0.035	0.032	0.047	0.034
Adjusted R2	-0.074	-0.078	-0.083	-0.068	-0.084
F Statistic	4.167*** (df = 4; 432)	3.811*** (df = 4; 418)	3.295** (df = 4; 404)	4.814*** (df = 4; 390)	3.298** (df = 4; 376)

=====

Note:
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9,
+ type = "text")

=====

Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	18.577 (35.550)	14.070 (35.579)	13.037 (35.611)	2.099 (35.326)	-1.900 (35.512)
GSD_rl	-103.151*** (34.432)	-99.314*** (35.092)	-83.116** (35.968)	-68.716* (36.540)	-53.069 (37.581)
pre_dis10	-6.734 (8.999)	-6.898 (9.083)	-8.082 (9.178)	-11.292 (9.203)	-14.772 (9.371)
discovery:GSD_rl	-81.397 (111.466)	-71.976 (111.615)	-76.630 (111.780)	-42.167 (110.959)	-66.978 (111.783)
Observations	408	393	378	363	348
R2	0.030	0.029	0.025	0.021	0.033
Adjusted R2	-0.090	-0.094	-0.101	-0.108	-0.096
F Statistic	2.837** (df = 4; 362)	2.592** (df = 4; 348)	2.100* (df = 4; 334)	1.694 (df = 4; 320)	2.619** (df = 4; 306)

=====

Note:
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4,
+ type = "text")

=====

Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	13.740 (12.594)	15.722 (13.011)	6.795 (13.862)	22.275 (15.115)	11.222 (16.248)
PLTV_xconst	-3.820** (1.547)	-3.009* (1.598)	-3.914** (1.703)	-3.119* (1.857)	-4.089** (1.996)
pre_dis10	-2.375 (6.518)	-3.374 (6.733)	-4.210 (7.174)	-8.234 (7.822)	-8.857 (8.409)
discovery:PLTV_xconst	-6.199 (4.054)	-6.369 (4.188)	1.154 (4.462)	-14.462*** (4.865)	-6.487 (5.230)
Observations	420	420	420	420	420
R2	0.026	0.019	0.020	0.045	0.021
Adjusted R2	-0.091	-0.100	-0.098	-0.070	-0.097
F Statistic (df = 4; 374)	2.481**	1.766	1.868	4.393***	1.976*

=====

Note:
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9,
+ type = "text")

=====

Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	11.844 (16.428)	11.804 (16.451)	10.196 (16.472)	13.755 (16.312)	10.162 (16.389)
PLTV_xconst	-4.091** (2.042)	-4.020* (2.068)	-3.351 (2.096)	-3.088 (2.105)	-1.467 (2.152)
pre_dis10	-9.525 (8.562)	-9.210 (8.642)	-10.178 (8.729)	-12.115 (8.729)	-15.570* (8.882)
discovery:PLTV_xconst	-7.299 (5.299)	-7.857 (5.318)	-8.150 (5.338)	-9.634* (5.300)	-12.919** (5.359)

=====

Observations	408	393	378	363	348
R2	0.023	0.024	0.024	0.029	0.047
Adjusted R2	-0.099	-0.099	-0.102	-0.099	-0.081
F Statistic	2.116* (df = 4; 362)	2.179* (df = 4; 348)	2.046* (df = 4; 334)	2.368* (df = 4; 320)	3.784*** (df = 4; 306)

Note: *p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4,
+           type = "text")
```

=====
Dependent variable:

	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-79.707*** (21.711)	-112.952*** (20.838)	-58.162*** (21.920)	-101.506*** (21.297)	-70.882*** (21.850)
WGI_ge	-14.798* (8.286)	-5.854 (8.172)	-2.633 (8.791)	-4.528 (8.648)	-9.530 (9.074)
pre_dis10	9.566 (9.880)	4.754 (10.170)	-2.604 (11.710)	-3.948 (11.533)	-4.263 (12.023)
discovery:WGI_ge	-67.368*** (24.985)	-97.183*** (23.981)	-45.108* (25.246)	-72.860*** (24.468)	-50.006** (25.041)

=====
Observations 360 348 333 318 303
R2 0.061 0.097 0.028 0.096 0.054
Adjusted R2 -0.061 -0.024 -0.105 -0.031 -0.082
F Statistic 5.121*** (df = 4; 318) 8.258*** (df = 4; 306) 2.116* (df = 4; 292) 7.359*** (df = 4; 278) 3.768*** (df = 4; 264)

Note: *p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9,
+           type = "text")
```

=====
Dependent variable:

	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	-27.890 (23.328)	-27.449 (23.070)	-9.840 (24.139)	-41.517* (23.448)	-106.250*** (24.545)
WGI_ge	-13.931 (9.813)	-19.646** (9.865)	-22.833** (10.580)	-24.041** (10.665)	-24.727** (10.712)
pre_dis10	-6.146 (13.095)	-6.520 (13.276)	-11.168 (14.347)	-16.615 (14.547)	-20.793 (14.931)
discovery:WGI_ge	-10.939 (26.660)	-4.234 (26.272)	17.346 (27.378)	-7.434 (26.461)	-67.911** (27.085)

=====
Observations 288 273 258 243 228
R2 0.020 0.035 0.037 0.068 0.154
Adjusted R2 -0.125 -0.112 -0.115 -0.084 0.010
F Statistic 1.304 (df = 4; 250) 2.145* (df = 4; 236) 2.120* (df = 4; 222) 3.821*** (df = 4; 208) 8.830*** (df = 4; 194)

Note: *p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4,
+           type = "text")
```

=====
Dependent variable:

	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-121.106*** (46.082)	-172.448*** (44.561)	-70.843 (46.462)	-137.292*** (45.206)	-96.217** (45.953)
WGI_rl	-34.586*** (9.524)	-27.077*** (9.508)	-24.788** (10.079)	-24.503** (9.961)	-26.982*** (10.261)
pre_dis10	9.227 (9.722)	2.492 (10.106)	-5.599 (11.590)	-7.131 (11.475)	-6.649 (11.910)
discovery:WGI_rl	-84.277** (40.900)	-120.918*** (39.549)	-41.480 (41.258)	-82.127** (40.108)	-56.766 (40.736)

Observations	360	348	333	318	303
R2	0.077	0.097	0.040	0.098	0.065
Adjusted R2	-0.043	-0.024	-0.091	-0.029	-0.070
F Statistic	6.591*** (df = 4; 318)	8.200*** (df = 4; 306)	3.057** (df = 4; 292)	7.549*** (df = 4; 278)	4.586*** (df = 4; 264)

Note:
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9,
+ type = "text")

Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	-25.422 (48.841)	-26.726 (48.210)	15.268 (50.372)	-47.267 (48.977)	-181.320*** (51.035)
WGI_rq	-25.237** (11.113)	-25.447** (11.265)	-21.486* (12.232)	-15.186 (12.261)	-8.693 (12.179)
pre_dis10	-7.359 (12.976)	-7.303 (13.200)	-11.933 (14.322)	-17.821 (14.621)	-24.066 (15.093)
discovery:WGI_rq	-4.402 (43.254)	-1.386 (42.651)	35.776 (44.516)	-10.008 (43.231)	-115.510** (44.459)

Observations 288 273 258 243 228
R2 0.031 0.039 0.032 0.051 0.127
Adjusted R2 -0.112 -0.108 -0.120 -0.104 -0.022
F Statistic 1.995* (df = 4; 250) 2.371* (df = 4; 236) 1.846 (df = 4; 222) 2.799** (df = 4; 208) 7.039*** (df = 4; 194)

Note:
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4,
+ type = "text")

Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-39.348*** (14.403)	-60.208*** (14.013)	-35.319** (14.512)	-68.393*** (14.085)	-52.494*** (14.332)
WGI_rq	-33.950*** (7.288)	-27.766*** (7.524)	-28.620*** (8.116)	-28.895*** (8.046)	-30.700*** (8.409)
pre_dis10	8.903 (9.647)	2.497 (10.102)	-5.126 (11.523)	-6.020 (11.352)	-5.111 (11.760)
discovery:WGI_rq	-23.266 (15.116)	-35.928** (14.727)	-19.758 (15.293)	-36.229** (14.800)	-32.093** (15.012)

Observations	360	348	333	318	303
R2	0.098	0.107	0.066	0.130	0.101
Adjusted R2	-0.018	-0.012	-0.062	0.008	-0.028
F Statistic	8.625*** (df = 4; 318)	9.184*** (df = 4; 306)	5.128*** (df = 4; 292)	10.413*** (df = 4; 278)	7.439*** (df = 4; 264)

Note:
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9,
+ type = "text")

Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	-32.792** (15.252)	-40.487*** (15.076)	-36.138** (15.884)	-51.987*** (15.472)	-70.779*** (15.384)
WGI_rq	-33.196*** (9.204)	-32.795*** (9.334)	-31.899*** (10.028)	-28.692*** (10.051)	-26.175** (10.238)
pre_dis10	-5.300 (12.786)	-4.038 (12.967)	-7.883 (14.111)	-15.013 (14.325)	-25.252* (15.003)
discovery:WGI_rq	-21.624 (15.916)	-25.693 (15.656)	-19.781 (16.409)	-23.823 (15.874)	-27.941* (15.528)

	288	273	258	243	228
R2	0.071	0.083	0.070	0.095	0.144
Adjusted R2	-0.066	-0.057	-0.077	-0.053	-0.002
F Statistic	4.810*** (df = 4; 250)	5.328*** (df = 4; 236)	4.169*** (df = 4; 222)	5.453*** (df = 4; 208)	8.162*** (df = 4; 194)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4,					
+ type = "text")					
<hr/>					
Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
<hr/>					
discovery	-66.234*** (17.958)	-63.646*** (18.027)	-21.489 (17.870)	-64.764*** (17.300)	-27.068 (17.846)
GSD_rl_pe	26.877 (16.586)	28.056* (16.939)	33.424* (17.150)	27.092 (17.015)	27.637 (18.036)
pre_dis10	0.871 (7.917)	-4.593 (8.208)	-6.168 (8.451)	-12.461 (8.216)	-9.612 (8.519)
discovery:GSD_rl_pe	139.034*** (43.242)	140.216*** (43.306)	60.818 (42.808)	124.475*** (41.376)	57.123 (42.616)
<hr/>					
Observations	483	468	453	438	423
R2	0.041	0.039	0.017	0.046	0.016
Adjusted R2	-0.070	-0.074	-0.099	-0.069	-0.104
F Statistic	4.585*** (df = 4; 432)	4.227*** (df = 4; 418)	1.786 (df = 4; 404)	4.689*** (df = 4; 390)	1.537 (df = 4; 376)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9,					
+ type = "text")					
<hr/>					
Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
<hr/>					
discovery	-25.432 (18.175)	-29.663 (18.248)	-32.674* (18.287)	-38.383** (18.140)	-55.210*** (18.522)
GSD_rl_pe	20.688 (18.921)	14.533 (19.607)	8.630 (20.319)	5.229 (20.979)	1.087 (22.117)
pre_dis10	-10.136 (8.730)	-10.211 (8.831)	-11.558 (8.930)	-14.202 (8.961)	-18.792** (9.184)
discovery:GSD_rl_pe	49.119 (43.332)	57.082 (43.428)	59.241 (43.436)	74.338* (42.989)	87.658** (43.339)
<hr/>					
Observations	408	393	378	363	348
R2	0.012	0.012	0.014	0.019	0.039
Adjusted R2	-0.111	-0.113	-0.113	-0.110	-0.090
F Statistic	1.123 (df = 4; 362)	1.086 (df = 4; 348)	1.166 (df = 4; 334)	1.564 (df = 4; 320)	3.074** (df = 4; 306)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4,					
+ type = "text")					
<hr/>					
Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
<hr/>					
discovery	24.895 (19.877)	15.175 (20.072)	4.972 (19.852)	21.855 (19.244)	12.930 (19.716)
VD_rl	-52.412*** (14.150)	-55.635*** (14.501)	-56.665*** (14.604)	-50.892*** (14.538)	-51.624*** (15.340)
pre_dis10	10.137 (8.056)	3.346 (8.419)	-4.297 (8.665)	-3.199 (8.454)	-5.997 (8.723)
discovery:VD_rl	-239.243**	-160.442	-15.730	-247.177**	-112.216

	(110.027)	(111.075)	(109.784)	(106.530)	(109.260)
Observations	483	468	453	438	423
R2	0.049	0.043	0.037	0.057	0.036
Adjusted R2	-0.061	-0.069	-0.077	-0.057	-0.082
F Statistic	5.597*** (df = 4; 432)	4.721*** (df = 4; 418)	3.876*** (df = 4; 404)	5.898*** (df = 4; 390)	3.469*** (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9,					
+ type = "text")					
Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	25.161 (19.962)	22.625 (19.987)	25.146 (19.933)	12.311 (19.809)	-0.863 (19.969)
VD_rl	-47.825*** (15.936)	-46.494*** (16.181)	-44.806*** (16.404)	-43.388*** (16.606)	-40.288** (17.136)
pre_dis10	-4.747 (8.901)	-4.722 (8.989)	-5.151 (9.051)	-9.274 (9.093)	-13.537 (9.272)
discovery:VD_rl	-198.412* (110.750)	-192.723* (111.027)	-223.769** (110.881)	-146.120 (110.362)	-136.096 (110.903)
Observations	408	393	378	363	348
R2	0.037	0.037	0.041	0.036	0.048
Adjusted R2	-0.082	-0.085	-0.083	-0.091	-0.080
F Statistic	3.523*** (df = 4; 362)	3.314** (df = 4; 348)	3.560*** (df = 4; 334)	2.948** (df = 4; 320)	3.834*** (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4,					
+ type = "text")					
Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-387.354*** (133.099)	-419.572*** (134.901)	-349.076** (140.597)	-546.766*** (136.867)	-403.892*** (133.267)
EFW	1.738 (6.083)	3.519 (6.420)	6.327 (6.879)	0.400 (7.004)	5.159 (7.023)
pre_dis10	12.031 (11.916)	6.049 (12.891)	3.675 (14.625)	-2.578 (14.717)	1.155 (14.924)
discovery:EFW	61.766*** (23.302)	66.829*** (23.605)	56.003** (24.588)	87.960*** (23.924)	64.865*** (23.282)
Observations	304	294	281	268	255
R2	0.072	0.082	0.043	0.116	0.081
Adjusted R2	-0.065	-0.059	-0.107	-0.026	-0.070
F Statistic	5.146*** (df = 4; 264)	5.649*** (df = 4; 254)	2.708** (df = 4; 242)	7.560*** (df = 4; 230)	4.830*** (df = 4; 218)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9,					
+ type = "text")					
Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	-545.034*** (135.036)	-756.655*** (129.762)	-768.846*** (134.112)	-827.232*** (137.696)	-628.934*** (143.150)
EFW	5.367 (7.301)	6.169 (7.220)	9.004 (7.569)	11.411 (7.920)	17.688** (7.751)
pre_dis10	-1.686 (15.918)	-4.728 (16.351)	-8.295 (18.509)	-23.219 (21.692)	-47.538* (26.340)

discovery:EFW	91.833*** (23.579)	128.610*** (22.647)	131.376*** (23.390)	140.119*** (23.999)	101.425*** (25.260)
<hr/>					
Observations	242	229	216	203	190
R2	0.093	0.171	0.175	0.207	0.218
Adjusted R2	-0.062	0.026	0.025	0.058	0.065
F Statistic	5.255*** (df = 4; 206)	10.030*** (df = 4; 194)	9.654*** (df = 4; 182)	11.085*** (df = 4; 170)	11.043*** (df = 4; 158)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")					
<hr/>					

Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-16.530 (116.686)	-11.935 (116.511)	17.873 (117.050)	43.420 (113.789)	44.421 (113.301)
IEF	-1.672*** (0.454)	-1.924*** (0.458)	-2.038*** (0.468)	-2.405*** (0.468)	-2.618*** (0.474)
pre_dis10	8.997 (9.622)	0.610 (10.288)	-4.553 (11.260)	-9.692 (11.178)	-8.830 (11.410)
discovery:IEF	-0.078 (2.305)	-0.260 (2.301)	-0.635 (2.311)	-1.534 (2.246)	-1.326 (2.237)
<hr/>					
Observations	378	364	350	336	322
R2	0.053	0.066	0.061	0.109	0.108
Adjusted R2	-0.076	-0.063	-0.071	-0.019	-0.022
F Statistic	4.632*** (df = 4; 332)	5.633*** (df = 4; 319)	4.985*** (df = 4; 306)	8.947*** (df = 4; 293)	8.490*** (df = 4; 280)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")					
<hr/>					

Dependent variable:					
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)
discovery	-5.186 (114.858)	-72.852 (115.799)	-64.589 (116.795)	-17.545 (115.694)	-16.468 (112.285)
IEF	-2.676*** (0.489)	-2.669*** (0.505)	-2.777*** (0.520)	-2.797*** (0.526)	-2.857*** (0.520)
pre_dis10	-7.045 (11.900)	-4.944 (12.414)	-5.889 (13.056)	-12.878 (13.628)	-22.106 (14.194)
discovery:IEF	-0.178 (2.267)	1.160 (2.286)	0.999 (2.306)	-0.093 (2.284)	-0.384 (2.220)
<hr/>					
Observations	308	294	280	266	252
R2	0.103	0.101	0.108	0.119	0.155
Adjusted R2	-0.031	-0.037	-0.033	-0.024	0.014
F Statistic	7.677*** (df = 4; 267)	7.162*** (df = 4; 254)	7.294*** (df = 4; 241)	7.728*** (df = 4; 228)	9.889*** (df = 4; 215)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")					
<hr/>					

Dependent variable:					
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)
discovery	-19.932 (52.301)	-14.373 (51.097)	3.912 (50.363)	-8.306 (50.456)	-3.296 (51.211)
CBIE	1.842 (24.098)	-7.605 (23.798)	-10.752 (23.743)	-11.829 (24.343)	-10.114 (25.341)
pre_dis10	4.866 (10.223)	-4.094 (10.490)	-10.373 (10.988)	-15.631 (11.129)	-13.092 (11.429)

discovery:CBIE	-3.673 (92.043)	-15.628 (90.015)	-22.478 (88.860)	-27.001 (88.977)	-10.708 (90.246)					
<hr/>										
Observations	387	374	361	348	335					
R2	0.016	0.016	0.005	0.021	0.007					
Adjusted R2	-0.124	-0.126	-0.141	-0.125	-0.144					
F Statistic	1.354 (df = 4; 338)	1.341 (df = 4; 326)	0.405 (df = 4; 314)	1.635 (df = 4; 302)	0.500 (df = 4; 290)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)					
<hr/>										
discovery	-1.682 (51.393)	19.086 (51.386)	26.691 (50.948)	28.615 (51.371)	32.045 (51.371)					
CBIE	-4.374 (25.983)	6.035 (26.629)	16.712 (27.128)	21.302 (28.246)	20.959 (29.323)					
pre_dis10	-11.769 (11.636)	-13.240 (11.830)	-16.646 (11.958)	-23.507* (12.335)	-30.798** (12.726)					
discovery:CBIE	-0.252 (90.524)	-39.717 (90.466)	-54.760 (89.648)	-67.236 (90.337)	-95.781 (90.382)					
<hr/>										
Observations	322	309	296	283	270					
R2	0.004	0.005	0.008	0.016	0.034					
Adjusted R2	-0.150	-0.152	-0.152	-0.146	-0.130					
F Statistic	0.297 (df = 4; 278)	0.317 (df = 4; 266)	0.528 (df = 4; 254)	1.007 (df = 4; 242)	2.037* (df = 4; 230)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4,										
+ type = "text")										
<hr/>										
Dependent variable:										
	RE (1)	RE1 (2)	RE2 (3)	RE3 (4)	RE4 (5)					
<hr/>										
discovery	90.436 (57.200)	182.733*** (56.374)	198.080*** (55.068)	15.879 (54.462)	30.438 (55.458)					
EcGI	0.420 (0.276)	0.653** (0.278)	0.610** (0.277)	0.509* (0.281)	0.501* (0.294)					
pre_dis10	4.265 (7.994)	-0.725 (8.144)	-4.260 (8.274)	-10.235 (8.244)	-9.814 (8.466)					
discovery:EcGI	-2.097* (1.109)	-3.855*** (1.093)	-3.884*** (1.067)	-0.703 (1.055)	-0.728 (1.074)					
<hr/>										
Observations	480	468	453	438	423					
R2	0.021	0.043	0.041	0.022	0.012					
Adjusted R2	-0.091	-0.069	-0.073	-0.095	-0.109					
F Statistic	2.264* (df = 4; 430)	4.685*** (df = 4; 418)	4.348*** (df = 4; 404)	2.234* (df = 4; 390)	1.123 (df = 4; 376)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	RE5 (1)	RE6 (2)	RE7 (3)	RE8 (4)	RE9 (5)					
<hr/>										
discovery	-146.452*** (55.754)	-153.038*** (55.663)	-193.479*** (55.208)	-76.508 (55.430)	-120.999** (55.441)					
EcGI	0.377 (0.305)	0.437 (0.314)	0.394 (0.327)	0.438 (0.343)	0.433 (0.360)					
pre_dis10	-11.800	-11.765	-12.984	-14.363	-18.467**					

	(8.587)	(8.657)	(8.681)	(8.818)	(8.958)
discovery:EcGI	2.717** (1.079)	2.817*** (1.077)	3.566*** (1.068)	1.271 (1.072)	1.913* (1.071)
<hr/>					
Observations	408	393	378	363	348
R2	0.027	0.031	0.045	0.020	0.041
Adjusted R2	-0.094	-0.091	-0.077	-0.109	-0.087
F Statistic	2.512** (df = 4; 362)	2.806** (df = 4; 348)	3.979*** (df = 4; 334)	1.591 (df = 4; 320)	3.299** (df = 4; 306)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				

2.3. Renewable energy excluding biofuels (RE_exbio)

Dependent variable:					
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	-37.153** (17.358)	-63.007*** (16.479)	-23.250 (16.845)	-47.061*** (16.627)	-39.360** (16.609)
WGI	-1.298 (0.916)	-0.337 (0.905)	-0.172 (0.944)	-0.399 (0.947)	-0.988 (0.964)
pre_dis10	0.780 (4.984)	-2.182 (5.093)	-6.502 (5.736)	-5.498 (5.763)	-4.875 (5.877)
discovery:WGI	-4.717 (3.209)	-8.295*** (3.051)	-2.285 (3.128)	-4.669 (3.084)	-4.389 (3.078)
<hr/>					
Observations	360	348	333	318	303
R2	0.033	0.075	0.022	0.079	0.053
Adjusted R2	-0.092	-0.049	-0.112	-0.050	-0.083
F Statistic	2.690** (df = 4; 318)	6.163*** (df = 4; 306)	1.658 (df = 4; 292)	5.981*** (df = 4; 278)	3.686*** (df = 4; 264)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model4.5,model4.6,model4.7,model4.8,model4.9, + type = "text")					

Dependent variable:					
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	-24.199 (17.350)	-28.169 (17.291)	-20.620 (18.043)	-46.439*** (17.262)	-58.628*** (16.998)
WGI	-1.351 (1.033)	-1.942* (1.059)	-1.892 (1.147)	-1.639 (1.140)	-1.491 (1.168)
pre_dis10	-4.787 (6.294)	-3.004 (6.464)	-3.710 (7.002)	-5.487 (7.030)	-4.285 (7.325)
discovery:WGI	-2.652 (3.212)	-3.297 (3.198)	-1.614 (3.333)	-4.898 (3.184)	-7.127** (3.114)
<hr/>					
Observations	288	273	258	243	228
R2	0.027	0.038	0.035	0.089	0.109
Adjusted R2	-0.117	-0.109	-0.118	-0.060	-0.042
F Statistic	1.726 (df = 4; 250)	2.329* (df = 4; 236)	1.989* (df = 4; 222)	5.049*** (df = 4; 208)	5.939*** (df = 4; 194)
<hr/>					

Note:
> stargazer(model5.0,model5.1,model5.2,model5.3,model5.4,
+ type = "text")

Dependent variable:					
	RE_exbio	RE_exbio1	RE_exbio2	RE_exbio3	RE_exbio4
	(1)	(2)	(3)	(4)	(5)
discovery	-30.019 (18.927)	-21.292 (20.922)	-13.664 (24.738)	16.558 (28.231)	17.835 (28.924)
SFI	-0.305 (0.404)	-0.457 (0.446)	-1.116** (0.528)	-1.190** (0.602)	-1.204* (0.617)

pre_dis10	-4.156 (3.510)	-4.901 (3.880)	-3.237 (4.588)	-3.378 (5.235)	-3.342 (5.364)					
discovery:SFI	2.185* (1.254)	1.355 (1.386)	1.123 (1.639)	-1.829 (1.871)	-1.690 (1.917)					
<hr/>										
Observations	360	360	360	360	360					
R2	0.015	0.009	0.018	0.036	0.026					
Adjusted R2	-0.112	-0.119	-0.108	-0.089	-0.100					
F Statistic (df = 4; 318)	1.224	0.725	1.492	2.942**	2.082*					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(mode15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)					
<hr/>										
discovery	4.678 (28.674)	-20.745 (28.779)	4.886 (29.535)	-13.871 (29.274)	2.718 (28.258)					
SFI	-1.236* (0.632)	-1.130* (0.667)	-0.830 (0.713)	0.075 (0.739)	1.041 (0.752)					
pre_dis10	-3.663 (5.412)	-4.147 (5.540)	-2.070 (5.821)	-5.387 (5.932)	-2.356 (5.913)					
discovery:SFI	-0.562 (1.899)	1.118 (1.905)	-0.590 (1.953)	0.226 (1.934)	-0.852 (1.869)					
<hr/>										
Observations	348	333	318	303	288					
R2	0.017	0.014	0.008	0.019	0.026					
Adjusted R2	-0.114	-0.122	-0.131	-0.122	-0.118					
F Statistic	1.342 (df = 4; 306)	0.999 (df = 4; 292)	0.585 (df = 4; 278)	1.283 (df = 4; 264)	1.669 (df = 4; 250)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(mode16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)					
<hr/>										
discovery	-17.320** (6.830)	-17.588** (6.944)	-3.066 (7.150)	-16.012** (7.237)	-5.938 (7.446)					
CSCI	-0.086 (1.177)	0.354 (1.212)	0.293 (1.262)	0.839 (1.292)	0.692 (1.346)					
pre_dis10	2.101 (3.841)	-0.313 (4.071)	-3.060 (4.408)	-2.744 (4.485)	-3.176 (4.640)					
discovery:CSCI	-12.502* (6.541)	-11.007 (6.682)	-2.415 (6.926)	-8.334 (7.002)	-4.091 (7.194)					
<hr/>										
Observations	469	454	439	424	409					
R2	0.016	0.017	0.003	0.017	0.005					
Adjusted R2	-0.102	-0.102	-0.120	-0.105	-0.122					
F Statistic	1.648 (df = 4; 418)	1.728 (df = 4; 404)	0.245 (df = 4; 390)	1.664 (df = 4; 376)	0.419 (df = 4; 362)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(mode16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)					
<hr/>										
discovery	-15.501** (7.583)	-13.590* (7.486)	-14.843** (7.418)	-21.431*** (7.290)	-17.627** (7.334)					
CSCI	0.400	0.253	0.307	0.294	0.375					

	(1.389)	(1.397)	(1.412)	(1.420)	(1.458)
pre_dis10	-0.465 (4.757)	0.036 (4.730)	0.469 (4.725)	-0.286 (4.687)	-1.355 (4.730)
discovery:CSCI	-14.624** (7.316)	-12.302* (7.211)	-12.997* (7.133)	-14.261** (6.998)	-10.434 (6.966)
Observations	394	379	364	349	334
R2	0.015	0.011	0.013	0.029	0.022
Adjusted R2	-0.113	-0.119	-0.119	-0.104	-0.116
F Statistic	1.291 (df = 4; 348)	0.943 (df = 4; 334)	1.088 (df = 4; 320)	2.272* (df = 4; 306)	1.614 (df = 4; 292)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
Dependent variable:					
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	17.505 (16.252)	20.771 (16.565)	5.458 (17.159)	12.831 (17.339)	7.431 (17.787)
GSD_rl	-27.634* (14.099)	-25.430* (14.725)	-27.015* (15.623)	-23.905 (16.200)	-25.991 (16.935)
pre_dis10	1.776 (3.740)	-0.031 (3.946)	-2.735 (4.253)	-2.517 (4.325)	-2.949 (4.468)
discovery:GSD_rl	-78.826 (50.980)	-94.040* (51.926)	-20.187 (53.732)	-69.929 (54.317)	-31.164 (55.747)
Observations	483	468	453	438	423
R2	0.022	0.025	0.010	0.022	0.010
Adjusted R2	-0.092	-0.089	-0.108	-0.095	-0.111
F Statistic	2.394** (df = 4; 432)	2.726** (df = 4; 418)	0.988 (df = 4; 404)	2.244* (df = 4; 390)	0.945 (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	13.845 (18.144)	11.444 (17.813)	12.193 (17.596)	16.424 (17.213)	9.202 (17.079)
GSD_rl	-22.645 (17.573)	-24.998 (17.569)	-22.283 (17.772)	-19.398 (17.805)	-16.829 (18.074)
pre_dis10	-2.032 (4.593)	-1.241 (4.548)	-0.905 (4.535)	-1.135 (4.484)	-2.027 (4.507)
discovery:GSD_rl	-55.308 (56.890)	-47.755 (55.881)	-52.468 (55.233)	-84.281 (54.066)	-58.615 (53.761)
Observations	408	393	378	363	348
R2	0.010	0.010	0.011	0.027	0.020
Adjusted R2	-0.113	-0.115	-0.117	-0.101	-0.111
F Statistic	0.946 (df = 4; 362)	0.918 (df = 4; 348)	0.891 (df = 4; 334)	2.183* (df = 4; 320)	1.590 (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4, + type = "text")					
Dependent variable:					
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	4.000 (4.837)	5.764 (5.279)	1.188 (6.575)	6.855 (7.699)	1.042 (8.214)

PLTV_xconst	0.748 (0.594)	1.264* (0.649)	0.892 (0.808)	1.399 (0.946)	0.846 (1.009)					
pre_dis10	-1.449 (2.503)	-2.091 (2.732)	-2.059 (3.403)	-3.352 (3.984)	-3.728 (4.251)					
discovery:PLTV_xconst	-0.980 (1.557)	-2.662 (1.699)	1.091 (2.116)	-5.330** (2.478)	-1.319 (2.644)					
<hr/>										
Observations	420	420	420	420	420					
R2	0.007	0.017	0.010	0.024	0.005					
Adjusted R2	-0.112	-0.102	-0.110	-0.093	-0.115					
F Statistic (df = 4; 374)	0.665	1.593	0.907	2.340*	0.466					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")										
<hr/>										
Dependent variable:										
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)					
<hr/>										
discovery	1.996 (8.374)	5.127 (8.232)	2.118 (8.158)	6.903 (7.952)	2.681 (7.928)					
PLTV_xconst	0.593 (1.041)	0.473 (1.035)	0.261 (1.038)	0.261 (1.026)	0.500 (1.041)					
pre_dis10	-3.371 (4.365)	-2.277 (4.325)	-2.115 (4.323)	-2.742 (4.256)	-3.067 (4.297)					
discovery:PLTV_xconst	-2.060 (2.701)	-3.283 (2.661)	-2.381 (2.644)	-6.388** (2.584)	-4.532* (2.593)					
<hr/>										
Observations	408	393	378	363	348					
R2	0.005	0.007	0.005	0.034	0.023					
Adjusted R2	-0.119	-0.119	-0.123	-0.093	-0.108					
F Statistic	0.463 (df = 4; 362)	0.600 (df = 4; 348)	0.451 (df = 4; 334)	2.782** (df = 4; 320)	1.828 (df = 4; 306)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4, + type = "text")										
<hr/>										
Dependent variable:										
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)					
<hr/>										
discovery	-34.098*** (10.912)	-58.041*** (10.190)	-22.865** (10.539)	-44.704*** (10.423)	-34.997*** (10.511)					
WGI_ge	-0.003 (4.165)	4.689 (3.996)	5.338 (4.227)	2.999 (4.232)	0.582 (4.365)					
pre_dis10	0.452 (4.966)	-2.004 (4.973)	-6.057 (5.630)	-5.382 (5.644)	-5.090 (5.784)					
discovery:WGI_ge	-27.438** (12.557)	-49.770*** (11.727)	-15.495 (12.138)	-28.503** (11.974)	-23.688* (12.046)					
<hr/>										
Observations	360	348	333	318	303					
R2	0.034	0.105	0.030	0.090	0.055					
Adjusted R2	-0.090	-0.015	-0.103	-0.038	-0.081					
F Statistic	2.803** (df = 4; 318)	8.958*** (df = 4; 306)	2.222* (df = 4; 292)	6.843*** (df = 4; 278)	3.832*** (df = 4; 264)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9, + type = "text")										
<hr/>										
Dependent variable:										
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)					
<hr/>										
discovery	-17.664 (11.093)	-7.699 (11.170)	-5.239 (11.678)	-32.283*** (11.265)	-51.348*** (11.837)					

WGI_ge	-0.700 (4.666)	-4.096 (4.777)	-5.071 (5.118)	-5.097 (5.124)	-6.016 (5.166)					
pre_dis10	-5.403 (6.227)	-5.178 (6.428)	-5.500 (6.941)	-6.660 (6.989)	-4.330 (7.201)					
discovery:WGI_ge	-9.152 (12.677)	4.765 (12.720)	9.278 (13.245)	-14.188 (12.712)	-36.650*** (13.062)					
<hr/>										
Observations	288	273	258	243	228					
R2	0.019	0.022	0.027	0.079	0.122					
Adjusted R2	-0.126	-0.128	-0.127	-0.072	-0.027					
F Statistic	1.217 (df = 4; 250)	1.304 (df = 4; 236)	1.512 (df = 4; 222)	4.442*** (df = 4; 208)	6.732*** (df = 4; 194)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4, + type = "text")										
<hr/>										
Dependent variable:										
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)					
<hr/>										
discovery	-48.288** (23.317)	-90.151*** (21.996)	-21.677 (22.558)	-50.151** (22.295)	-39.932* (22.279)					
WGI_rl	-9.109* (4.819)	-5.437 (4.693)	-3.403 (4.893)	-3.619 (4.913)	-6.393 (4.975)					
pre_dis10	-0.308 (4.919)	-3.625 (4.988)	-7.374 (5.627)	-6.834 (5.659)	-6.339 (5.774)					
discovery:WGI_rl	-31.621 (20.695)	-63.214*** (19.522)	-9.004 (20.032)	-24.385 (19.781)	-20.570 (19.750)					
<hr/>										
Observations	360	348	333	318	303					
R2	0.038	0.087	0.023	0.078	0.051					
Adjusted R2	-0.086	-0.035	-0.111	-0.052	-0.086					
F Statistic	3.115** (df = 4; 318)	7.318*** (df = 4; 306)	1.688 (df = 4; 292)	5.858*** (df = 4; 278)	3.550*** (df = 4; 264)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9, + type = "text")										
<hr/>										
Dependent variable:										
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)					
<hr/>										
discovery	-13.266 (23.335)	-0.208 (23.339)	13.597 (24.292)	-37.341 (23.421)	-88.220*** (24.392)					
WGI_rl	-5.066 (5.310)	-6.690 (5.454)	-3.906 (5.899)	-2.703 (5.863)	0.026 (5.821)					
pre_dis10	-6.162 (6.200)	-5.340 (6.390)	-5.925 (6.907)	-7.560 (6.991)	-5.706 (7.213)					
discovery:WGI_rl	-2.087 (20.666)	10.460 (20.647)	23.738 (21.467)	-14.556 (20.673)	-59.370*** (21.249)					
<hr/>										
Observations	288	273	258	243	228					
R2	0.020	0.025	0.028	0.070	0.110					
Adjusted R2	-0.125	-0.123	-0.125	-0.082	-0.042					
F Statistic	1.301 (df = 4; 250)	1.543 (df = 4; 236)	1.601 (df = 4; 222)	3.922*** (df = 4; 208)	5.981*** (df = 4; 194)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4, + type = "text")										
<hr/>										
Dependent variable:										
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)					
<hr/>										
discovery	-17.714**	-31.340***	-15.750**	-32.610***	-26.831***					

	(7.320)	(6.976)	(7.094)	(6.989)	(7.015)
WGI_rq	-11.043*** (3.704)	-7.285* (3.746)	-7.262* (3.967)	-7.931** (3.993)	-7.232* (4.116)
pre_dis10	-0.523 (4.903)	-3.750 (5.029)	-7.163 (5.633)	-6.144 (5.633)	-5.235 (5.756)
discovery:WGI_rq	-8.343 (7.682)	-17.063** (7.332)	-6.794 (7.475)	-14.653** (7.344)	-15.193** (7.348)
Observations	360	348	333	318	303
R2	0.052	0.082	0.036	0.100	0.070
Adjusted R2	-0.071	-0.041	-0.097	-0.026	-0.063
F Statistic	4.332*** (df = 4; 318)	6.851*** (df = 4; 306)	2.689** (df = 4; 292)	7.709*** (df = 4; 278)	5.000*** (df = 4; 264)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9, + type = "text")					
Dependent variable:					
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	-18.126** (7.359)	-20.306*** (7.382)	-20.997*** (7.735)	-33.107*** (7.451)	-33.376*** (7.442)
WGI_rq	-8.594* (4.441)	-8.574* (4.570)	-8.170* (4.884)	-6.230 (4.840)	-4.882 (4.953)
pre_dis10	-4.919 (6.170)	-3.053 (6.349)	-3.030 (6.872)	-5.607 (6.898)	-5.630 (7.258)
discovery:WGI_rq	-11.354 (7.680)	-13.518* (7.666)	-12.788 (7.991)	-17.441** (7.644)	-17.012** (7.512)
Observations	288	273	258	243	228
R2	0.043	0.049	0.047	0.101	0.106
Adjusted R2	-0.099	-0.096	-0.103	-0.046	-0.046
F Statistic	2.780** (df = 4; 250)	3.030** (df = 4; 236)	2.761** (df = 4; 222)	5.814*** (df = 4; 208)	5.751*** (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4, + type = "text")					
Dependent variable:					
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	-23.748*** (8.244)	-28.676*** (8.345)	-5.097 (8.631)	-22.759*** (8.725)	-4.402 (9.004)
GSD_rl_pe	-3.601 (7.614)	-1.928 (7.842)	3.288 (8.283)	3.554 (8.582)	5.862 (9.100)
pre_dis10	-1.435 (3.634)	-4.131 (3.800)	-3.743 (4.082)	-5.614 (4.144)	-3.932 (4.298)
discovery:GSD_rl_pe	46.242** (19.852)	55.666*** (20.048)	10.946 (20.676)	37.604* (20.868)	5.234 (21.501)
Observations	483	468	453	438	423
R2	0.019	0.028	0.003	0.022	0.004
Adjusted R2	-0.094	-0.086	-0.115	-0.096	-0.118
F Statistic	2.126* (df = 4; 432)	3.027** (df = 4; 418)	0.314 (df = 4; 404)	2.165* (df = 4; 390)	0.387 (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9, + type = "text")					
Dependent variable:					
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)

discovery	-3.269 (9.223)	-6.668 (9.093)	-6.414 (9.020)	-22.620** (8.844)	-15.160* (8.954)					
GSD_rl_pe	4.148 (9.602)	2.675 (9.770)	1.416 (10.022)	-0.366 (10.228)	1.775 (10.692)					
pre_dis10	-3.442 (4.430)	-2.735 (4.400)	-2.455 (4.404)	-4.339 (4.369)	-3.858 (4.440)					
discovery:GSD_rl_pe	-0.442 (21.988)	8.836 (21.639)	6.408 (21.423)	35.521* (20.958)	16.984 (20.952)					
<hr/>										
Observations	408	393	378	363	348					
R2	0.003	0.003	0.003	0.024	0.016					
Adjusted R2	-0.120	-0.123	-0.125	-0.104	-0.116					
F Statistic	0.310 (df = 4; 362)	0.270 (df = 4; 348)	0.275 (df = 4; 334)	1.966* (df = 4; 320)	1.230 (df = 4; 306)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)					
<hr/>										
discovery	12.105 (9.121)	9.703 (9.313)	6.162 (9.657)	9.249 (9.739)	6.134 (10.033)					
VD_rl	-13.343** (6.493)	-11.601* (6.728)	-10.412 (7.104)	-8.013 (7.358)	-6.609 (7.806)					
pre_dis10	2.339 (3.697)	0.038 (3.906)	-2.388 (4.215)	-1.813 (4.279)	-2.679 (4.439)					
discovery:VD_rl	-116.798** (50.489)	-111.113** (51.535)	-43.233 (53.406)	-111.938** (53.915)	-52.286 (55.598)					
<hr/>										
Observations	483	468	453	438	423					
R2	0.029	0.028	0.009	0.026	0.007					
Adjusted R2	-0.084	-0.086	-0.109	-0.091	-0.114					
F Statistic	3.212** (df = 4; 432)	3.039** (df = 4; 418)	0.903 (df = 4; 404)	2.644** (df = 4; 390)	0.665 (df = 4; 376)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)					
<hr/>										
discovery	14.297 (10.208)	14.159 (10.028)	15.444 (9.894)	13.815 (9.669)	4.189 (9.672)					
VD_rl	-4.129 (8.149)	-4.425 (8.119)	-4.398 (8.143)	-3.856 (8.105)	-3.826 (8.299)					
pre_dis10	-0.960 (4.551)	0.035 (4.510)	0.589 (4.493)	0.185 (4.438)	-1.583 (4.491)					
discovery:VD_rl	-109.236* (56.632)	-108.852* (55.708)	-121.201** (55.041)	-145.782*** (53.868)	-81.349 (53.712)					
<hr/>										
Observations	408	393	378	363	348					
R2	0.014	0.014	0.018	0.038	0.022					
Adjusted R2	-0.109	-0.111	-0.108	-0.088	-0.110					
F Statistic	1.272 (df = 4; 362)	1.242 (df = 4; 348)	1.545 (df = 4; 334)	3.156** (df = 4; 320)	1.687 (df = 4; 306)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)					

	-257.806*** (62.828)	-192.818*** (66.625)	-196.204*** (68.765)	-271.686*** (65.795)	-179.231*** (65.228)
EFW	2.354 (2.871)	2.630 (3.171)	4.098 (3.364)	0.754 (3.367)	2.611 (3.437)
pre_dis10	-3.894 (5.625)	-6.201 (6.367)	-8.484 (7.153)	-9.596 (7.075)	-6.303 (7.305)
discovery:EFW	42.101*** (10.999)	30.093** (11.658)	32.599*** (12.026)	43.225*** (11.591)	28.015** (11.396)
Observations	304	294	281	268	255
R2	0.099	0.085	0.055	0.136	0.085
Adjusted R2	-0.034	-0.055	-0.094	-0.003	-0.066
F Statistic	7.232*** (df = 4; 264)	5.912*** (df = 4; 254)	3.497*** (df = 4; 242)	9.018*** (df = 4; 230)	5.056*** (df = 4; 218)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					
<hr/>					
	Dependent variable:				
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	-148.072** (67.028)	-374.258*** (61.697)	-290.047*** (68.177)	-384.652*** (68.400)	-207.400*** (72.273)
EFW	3.850 (3.624)	4.243 (3.433)	5.671 (3.848)	6.057 (3.934)	10.946*** (3.913)
pre_dis10	-5.825 (7.901)	-8.555 (7.774)	-7.345 (9.409)	-15.608 (10.775)	-16.629 (13.298)
discovery:EFW	23.695** (11.704)	63.118*** (10.768)	48.635*** (11.890)	63.730*** (11.921)	32.417** (12.753)
Observations	242	229	216	203	190
R2	0.053	0.192	0.124	0.211	0.167
Adjusted R2	-0.108	0.051	-0.035	0.063	0.004
F Statistic	2.857** (df = 4; 206)	11.545*** (df = 4; 194)	6.414*** (df = 4; 182)	11.376*** (df = 4; 170)	7.918*** (df = 4; 158)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")					
<hr/>					
	Dependent variable:				
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	-36.508 (60.027)	-14.870 (60.775)	7.770 (60.154)	18.354 (58.452)	17.728 (57.997)
IEF	-0.428* (0.234)	-0.485** (0.239)	-0.434* (0.241)	-0.586** (0.240)	-0.682*** (0.243)
pre_dis10	0.077 (4.950)	-4.043 (5.366)	-5.941 (5.787)	-7.628 (5.742)	-6.815 (5.841)
discovery:IEF	0.568 (1.186)	0.069 (1.200)	-0.245 (1.188)	-0.676 (1.154)	-0.550 (1.145)
Observations	378	364	350	336	322
R2	0.017	0.025	0.014	0.049	0.040
Adjusted R2	-0.117	-0.109	-0.124	-0.087	-0.101
F Statistic	1.395 (df = 4; 332)	2.056* (df = 4; 319)	1.116 (df = 4; 306)	3.814*** (df = 4; 293)	2.891** (df = 4; 280)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")					
<hr/>					
	Dependent variable:				
	RE_exbio5	RE_exbio6	RE_exbio7	RE_exbio8	RE_exbio9

	(1)	(2)	(3)	(4)	(5)
discovery	22.954 (57.743)	-21.417 (57.754)	-16.725 (58.787)	16.796 (57.655)	1.074 (56.483)
IEF	-0.624** (0.246)	-0.652** (0.252)	-0.706*** (0.262)	-0.648** (0.262)	-0.611** (0.262)
pre_dis10	-4.952 (5.983)	-2.932 (6.191)	-2.389 (6.571)	-6.408 (6.791)	-5.703 (7.140)
discovery:IEF	-0.569 (1.140)	0.308 (1.140)	0.207 (1.160)	-0.614 (1.138)	-0.280 (1.117)
Observations	308	294	280	266	252
R2	0.029	0.029	0.033	0.053	0.048
Adjusted R2	-0.117	-0.120	-0.120	-0.101	-0.111
F Statistic	1.963 (df = 4; 267)	1.882 (df = 4; 254)	2.027* (df = 4; 241)	3.185** (df = 4; 228)	2.711** (df = 4; 215)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")					
Dependent variable:					
	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	-24.742 (24.244)	-20.386 (24.639)	-12.044 (25.272)	-21.910 (25.576)	-25.219 (26.132)
CBIE	-23.496** (11.170)	-25.829** (11.476)	-24.463** (11.914)	-27.609** (12.339)	-29.786** (12.931)
pre_dis10	1.829 (4.739)	-2.492 (5.058)	-4.381 (5.514)	-5.451 (5.641)	-3.114 (5.832)
discovery:CBIE	33.505 (42.666)	20.862 (43.406)	19.476 (44.590)	21.196 (45.102)	39.583 (46.051)
Observations	387	374	361	348	335
R2	0.017	0.024	0.016	0.029	0.021
Adjusted R2	-0.122	-0.116	-0.128	-0.115	-0.128
F Statistic	1.471 (df = 4; 338)	2.034* (df = 4; 326)	1.313 (df = 4; 314)	2.269* (df = 4; 302)	1.551 (df = 4; 290)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")					
Dependent variable:					
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	-26.396 (25.766)	-17.908 (25.554)	-19.804 (25.236)	-24.436 (24.914)	-18.861 (24.997)
CBIE	-26.968** (13.027)	-24.042* (13.242)	-23.324* (13.437)	-22.563 (13.699)	-19.916 (14.268)
pre_dis10	-1.461 (5.834)	-0.660 (5.883)	-0.428 (5.923)	-3.250 (5.983)	-2.508 (6.192)
discovery:CBIE	48.488 (45.385)	31.880 (44.988)	33.874 (44.404)	30.956 (43.813)	22.042 (43.979)
Observations	322	309	296	283	270
R2	0.018	0.013	0.013	0.019	0.015
Adjusted R2	-0.134	-0.142	-0.147	-0.143	-0.152
F Statistic	1.296 (df = 4; 278)	0.896 (df = 4; 266)	0.819 (df = 4; 254)	1.194 (df = 4; 242)	0.867 (df = 4; 230)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
Dependent variable:					

	RE_exbio (1)	RE_exbio1 (2)	RE_exbio2 (3)	RE_exbio3 (4)	RE_exbio4 (5)
discovery	-60.193** (25.987)	-42.009 (26.341)	-17.664 (26.929)	-20.588 (27.252)	-12.256 (27.929)
EcGI	-0.152 (0.125)	-0.019 (0.130)	-0.040 (0.136)	-0.060 (0.141)	-0.063 (0.148)
pre_dis10	-0.043 (3.632)	-2.714 (3.806)	-3.517 (4.046)	-4.485 (4.125)	-3.853 (4.264)
discovery:EcGI	1.050** (0.504)	0.657 (0.511)	0.328 (0.522)	0.230 (0.528)	0.196 (0.541)
Observations	480	468	453	438	423
R2	0.020	0.014	0.003	0.013	0.003
Adjusted R2	-0.092	-0.101	-0.115	-0.106	-0.118
F Statistic	2.140* (df = 4; 430)	1.494 (df = 4; 418)	0.301 (df = 4; 404)	1.313 (df = 4; 390)	0.326 (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	RE_exbio5 (1)	RE_exbio6 (2)	RE_exbio7 (3)	RE_exbio8 (4)	RE_exbio9 (5)
discovery	-110.266*** (27.920)	-95.087*** (27.553)	-103.043*** (27.110)	-92.738*** (26.706)	-75.383*** (26.562)
EcGI	-0.152 (0.153)	-0.140 (0.156)	-0.172 (0.160)	-0.190 (0.165)	-0.184 (0.173)
pre_dis10	-4.075 (4.300)	-2.900 (4.285)	-2.523 (4.263)	-3.314 (4.248)	-3.357 (4.292)
discovery:EcGI	2.100*** (0.540)	1.801*** (0.533)	1.944*** (0.524)	1.634*** (0.516)	1.308** (0.513)
Observations	408	393	378	363	348
R2	0.044	0.035	0.044	0.047	0.036
Adjusted R2	-0.075	-0.087	-0.079	-0.078	-0.093
F Statistic	4.164*** (df = 4; 362)	3.153** (df = 4; 348)	3.828*** (df = 4; 334)	3.955*** (df = 4; 320)	2.863** (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				

2.4. FE per capita

	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
discovery	-38.547** (15.231)	-33.594** (15.425)	-53.943*** (15.395)	-28.438* (15.430)	-16.762 (15.800)
WGI	0.468 (0.803)	0.914 (0.847)	1.327 (0.863)	1.581* (0.879)	1.544* (0.917)
pre_dis10	-2.980 (4.374)	7.661 (4.768)	17.105*** (5.242)	17.634*** (5.348)	14.640*** (5.591)
discovery:WGI	-4.278 (2.816)	-3.927 (2.856)	-9.184*** (2.858)	-4.378 (2.862)	-3.279 (2.928)
Observations	360	348	333	318	303
R2	0.047	0.045	0.072	0.060	0.036
Adjusted R2	-0.076	-0.083	-0.056	-0.071	-0.102
F Statistic	3.918*** (df = 4; 318)	3.620*** (df = 4; 306)	5.622*** (df = 4; 292)	4.475*** (df = 4; 278)	2.491** (df = 4; 264)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					

Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	-21.643 (15.898)	-7.702 (15.811)	9.926 (15.939)	29.787* (15.379)	20.160 (16.275)
WGI	0.971 (0.947)	1.031 (0.968)	1.104 (1.013)	1.622 (1.015)	0.604 (1.119)
pre_dis10	16.195*** (5.767)	12.570** (5.910)	10.317* (6.185)	2.683 (6.264)	0.210 (7.013)
discovery:WGI	-4.654 (2.943)	-2.011 (2.924)	1.137 (2.944)	5.286* (2.837)	3.498 (2.982)
Observations	288	273	258	243	228
R2	0.037	0.023	0.022	0.036	0.010
Adjusted R2	-0.105	-0.125	-0.132	-0.122	-0.158
F Statistic	2.418** (df = 4; 250)	1.420 (df = 4; 236)	1.235 (df = 4; 222)	1.916 (df = 4; 208)	0.511 (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model5.0,model5.1,model5.2,model5.3,model5.4, + type = "text")					
Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
discovery	41.542* (22.148)	53.170** (22.134)	58.664** (23.169)	52.045** (24.454)	40.229 (26.532)
SFI	0.108 (0.472)	0.248 (0.472)	0.560 (0.494)	1.014* (0.521)	1.578*** (0.566)
pre_dis10	16.880*** (4.107)	23.923*** (4.105)	21.027*** (4.297)	22.481*** (4.535)	18.790*** (4.920)
discovery:SFI	-3.274** (1.468)	-3.873*** (1.467)	-3.997*** (1.535)	-3.513** (1.620)	-2.452 (1.758)
Observations	360	360	360	360	360
R2	0.079	0.117	0.081	0.087	0.067
Adjusted R2	-0.040	0.003	-0.038	-0.031	-0.053
F Statistic (df = 4; 318)	6.825***	10.550***	7.006***	7.579***	5.698***
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model5.5,model5.6,model5.7,model5.8,model5.9, + type = "text")					
Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	36.988 (26.941)	49.358* (26.882)	34.285 (26.501)	2.145 (25.970)	-1.619 (25.944)
SFI	1.497** (0.594)	0.997 (0.623)	1.182* (0.640)	1.179* (0.655)	1.554** (0.690)
pre_dis10	19.795*** (5.085)	22.624*** (5.175)	20.740*** (5.223)	12.714** (5.262)	3.562 (5.428)
discovery:SFI	-2.050 (1.784)	-2.859 (1.779)	-1.957 (1.752)	0.167 (1.715)	0.357 (1.716)
Observations	348	333	318	303	288
R2	0.068	0.069	0.064	0.038	0.025
Adjusted R2	-0.057	-0.058	-0.067	-0.101	-0.120
F Statistic	5.561*** (df = 4; 306)	5.449*** (df = 4; 292)	4.786*** (df = 4; 278)	2.595** (df = 4; 264)	1.587 (df = 4; 250)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model6.0,model6.1,model6.2,model6.3,model6.4, + type = "text")					

Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
discovery	-19.611*** (7.170)	-18.104*** (6.823)	-19.013*** (6.572)	-16.051** (6.464)	-9.050 (6.539)
CSCI	-1.073 (1.236)	0.083 (1.191)	1.069 (1.160)	1.182 (1.154)	1.173 (1.182)
pre_dis10	7.405* (4.033)	16.996*** (4.000)	25.848*** (4.051)	27.363*** (4.006)	26.517*** (4.075)
discovery:CSCI	-10.555 (6.867)	-12.680* (6.565)	-21.301*** (6.366)	-19.191*** (6.254)	-18.142*** (6.318)
Observations	469	454	439	424	409
R2	0.030	0.057	0.100	0.114	0.106
Adjusted R2	-0.086	-0.058	-0.010	0.003	-0.007
F Statistic	3.279** (df = 4; 418)	6.071*** (df = 4; 404)	10.879*** (df = 4; 390)	12.053*** (df = 4; 376)	10.745*** (df = 4; 362)
Note: > stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")					
*p<0.1; **p<0.05; ***p<0.01					
Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	-6.903 (6.527)	-4.059 (6.557)	-2.128 (6.537)	3.914 (6.571)	1.495 (6.709)
CSCI	1.094 (1.196)	1.128 (1.224)	1.664 (1.244)	2.178* (1.280)	2.633** (1.333)
pre_dis10	28.709*** (4.095)	28.955*** (4.143)	29.308*** (4.164)	27.657*** (4.225)	25.648*** (4.327)
discovery:CSCI	-19.451*** (6.297)	-15.653** (6.316)	-11.877* (6.286)	-6.375 (6.308)	-10.957* (6.372)
Observations	394	379	364	349	334
R2	0.128	0.130	0.137	0.134	0.118
Adjusted R2	0.015	0.016	0.021	0.015	-0.006
F Statistic	12.770*** (df = 4; 348)	12.518*** (df = 4; 334)	12.712*** (df = 4; 320)	11.793*** (df = 4; 306)	9.784*** (df = 4; 292)
Note: > stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
*p<0.1; **p<0.05; ***p<0.01					
Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
discovery	32.119* (17.156)	30.356* (16.445)	56.375*** (15.891)	36.413** (15.672)	44.627*** (15.749)
GSD_rl	-16.882 (14.883)	-4.511 (14.618)	0.026 (14.468)	-0.696 (14.642)	-1.216 (14.994)
pre_dis10	9.082** (3.948)	17.744*** (3.918)	26.090*** (3.939)	26.208*** (3.909)	25.685*** (3.956)
discovery:GSD_rl	-139.066** (53.817)	-122.579** (51.548)	-186.689*** (49.760)	-118.009** (49.095)	-124.579** (49.359)
Observations	483	468	453	438	423
R2	0.041	0.062	0.106	0.106	0.102
Adjusted R2	-0.070	-0.048	0.0003	-0.002	-0.008
F Statistic	4.607*** (df = 4; 432)	6.877*** (df = 4; 418)	12.035*** (df = 4; 404)	11.509*** (df = 4; 390)	10.670*** (df = 4; 376)
Note: > stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
*p<0.1; **p<0.05; ***p<0.01					

Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	48.583*** (15.662)	21.133 (15.730)	-4.630 (15.579)	-5.209 (15.550)	15.920 (15.792)
GSD_rl	-3.815 (15.170)	-3.861 (15.514)	1.115 (15.736)	10.397 (16.085)	7.057 (16.713)
pre_dis10	27.522*** (3.965)	26.210*** (4.016)	25.074*** (4.015)	24.221*** (4.051)	22.601*** (4.167)
discovery:GSD_rl	-127.077** (49.108)	-39.167 (49.346)	40.446 (48.903)	47.312 (48.843)	-16.867 (49.711)
Observations	408	393	378	363	348
R2	0.122	0.116	0.127	0.127	0.100
Adjusted R2	0.012	0.005	0.014	0.013	-0.021
F Statistic	12.525*** (df = 4; 362)	11.460*** (df = 4; 348)	12.094*** (df = 4; 334)	11.656*** (df = 4; 320)	8.500*** (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4, + type = "text")					
Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
discovery	-11.276* (6.799)	-9.570 (6.361)	1.523 (6.395)	2.987 (6.615)	14.623** (7.168)
PLTV_xconst	1.617* (0.835)	1.473* (0.782)	1.174 (0.786)	0.852 (0.813)	0.655 (0.881)
pre_dis10	17.213*** (3.518)	21.414*** (3.292)	20.270*** (3.310)	22.646*** (3.423)	22.726*** (3.710)
discovery:PLTV_xconst	2.060 (2.188)	2.306 (2.048)	-0.204 (2.058)	-0.696 (2.129)	-3.265 (2.307)
Observations	420	420	420	420	420
R2	0.085	0.122	0.096	0.107	0.095
Adjusted R2	-0.025	0.017	-0.013	-0.0002	-0.014
F Statistic (df = 4; 374)	8.707***	13.048***	9.924***	11.233***	9.816***
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")					
Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	23.297*** (7.224)	20.136*** (7.226)	14.064* (7.194)	17.352** (7.201)	24.282*** (7.278)
PLTV_xconst	0.199 (0.898)	-0.177 (0.908)	-0.519 (0.915)	-0.464 (0.929)	-0.432 (0.956)
pre_dis10	24.597*** (3.765)	25.482*** (3.796)	26.262*** (3.813)	25.699*** (3.853)	22.633*** (3.944)
discovery:PLTV_xconst	-5.376** (2.330)	-4.283* (2.336)	-2.411 (2.331)	-3.102 (2.340)	-5.327** (2.380)
Observations	408	393	378	363	348
R2	0.118	0.124	0.129	0.129	0.116
Adjusted R2	0.008	0.013	0.017	0.017	-0.003

F Statistic	12.107*** (df = 4; 362)	12.271*** (df = 4; 348)	12.352*** (df = 4; 334)	11.898*** (df = 4; 320)	10.000*** (df = 4; 306)					
<hr/>										
Note:	*p<0.1; **p<0.05;									
***p<0.01										
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4,										
+ type = "text")										
<hr/>										
Dependent variable:										
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)					
-----	-----	-----	-----	-----	-----					
discovery	-18.226* (9.617)	-15.793 (9.742)	-23.398** (9.796)	-11.774 (9.804)	-6.949 (10.053)					
WGI_ge	-1.128 (3.671)	1.041 (3.821)	3.235 (3.929)	2.571 (3.981)	4.268 (4.175)					
pre_dis10	-4.156 (4.377)	6.670 (4.754)	14.808*** (5.233)	16.383*** (5.309)	14.050** (5.532)					
discovery:WGI_ge	-2.209 (11.068)	-3.391 (11.211)	-22.155* (11.282)	-7.929 (11.264)	-9.586 (11.521)					
-----	-----	-----	-----	-----	-----					
Observations	360	348	333	318	303					
R2	0.040	0.037	0.047	0.046	0.028					
Adjusted R2	-0.084	-0.092	-0.084	-0.088	-0.112					
F Statistic	3.297** (df = 4; 318)	2.912** (df = 4; 306)	3.580*** (df = 4; 292)	3.326** (df = 4; 278)	1.902 (df = 4; 264)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)					
-----	-----	-----	-----	-----	-----					
discovery	-13.798 (10.090)	-8.469 (10.018)	3.370 (10.083)	10.649 (9.889)	0.635 (11.415)					
WGI_ge	6.556 (4.244)	10.383** (4.284)	13.809*** (4.419)	13.371*** (4.498)	6.846 (4.982)					
pre_dis10	15.896*** (5.664)	12.884** (5.765)	10.691* (5.993)	3.904 (6.135)	1.653 (6.944)					
discovery:WGI_ge	-21.433* (11.531)	-15.109 (11.408)	-1.673 (11.436)	10.007 (11.159)	-1.789 (12.596)					
-----	-----	-----	-----	-----	-----					
Observations	288	273	258	243	228					
R2	0.044	0.045	0.058	0.054	0.011					
Adjusted R2	-0.098	-0.101	-0.091	-0.101	-0.158					
F Statistic	2.859** (df = 4; 250)	2.753** (df = 4; 236)	3.389** (df = 4; 222)	2.945** (df = 4; 208)	0.525 (df = 4; 194)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4,										
+ type = "text")										
<hr/>										
Dependent variable:										
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)					
-----	-----	-----	-----	-----	-----					
discovery	-22.558 (20.527)	-15.617 (20.717)	-42.908** (20.788)	-16.913 (20.756)	-11.591 (21.271)					
WGI_rl	6.051 (4.242)	8.088* (4.420)	9.086** (4.510)	7.450 (4.574)	4.931 (4.750)					
pre_dis10	-3.728 (4.331)	6.831 (4.698)	14.808*** (5.186)	16.448*** (5.269)	13.836** (5.513)					
discovery:WGI_rl	-5.902 (18.218)	-2.631 (18.386)	-33.614* (18.460)	-10.557 (18.416)	-11.001 (18.856)					

Observations	360	348	333	318	303
R2	0.046	0.047	0.056	0.053	0.028
Adjusted R2	-0.077	-0.081	-0.073	-0.080	-0.112
F Statistic	3.805*** (df = 4; 318)	3.745*** (df = 4; 306)	4.356*** (df = 4; 292)	3.883*** (df = 4; 278)	1.871 (df = 4; 264)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9,					
+ type = "text")					

Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	-24.477 (21.378)	-13.285 (21.239)	13.796 (21.444)	28.912 (20.902)	10.243 (23.466)
WGI_rq	1.429 (4.864)	1.437 (4.963)	-0.792 (5.207)	0.926 (5.233)	-0.487 (5.600)
pre_dis10	15.167*** (5.680)	12.408** (5.815)	10.674* (6.097)	4.540 (6.240)	1.974 (6.940)
discovery:WGI_rq	-24.446 (18.932)	-14.567 (18.790)	8.865 (18.950)	23.968 (18.450)	7.344 (20.442)

Observations	288	273	258	243	228
R2	0.031	0.020	0.017	0.013	0.002
Adjusted R2	-0.112	-0.129	-0.139	-0.149	-0.168
F Statistic	2.017* (df = 4; 250)	1.213 (df = 4; 236)	0.931 (df = 4; 222)	0.670 (df = 4; 208)	0.084 (df = 4; 194)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4,					
+ type = "text")					

Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
discovery	-21.166*** (6.482)	-17.987*** (6.576)	-18.843*** (6.583)	-11.050* (6.606)	-3.934 (6.772)
WGI_rq	-3.923 (3.280)	-0.801 (3.531)	0.170 (3.682)	0.480 (3.774)	-1.574 (3.973)
pre_dis10	-3.769 (4.342)	6.996 (4.748)	15.395*** (5.227)	16.721*** (5.325)	13.940** (5.557)
discovery:WGI_rq	-7.556 (6.803)	-7.067 (6.911)	-18.170*** (6.937)	-7.665 (6.942)	-6.062 (7.093)

Observations	360	348	333	318	303
R2	0.048	0.040	0.056	0.047	0.026
Adjusted R2	-0.074	-0.089	-0.074	-0.087	-0.114
F Statistic	4.033*** (df = 4; 318)	3.176** (df = 4; 306)	4.301*** (df = 4; 292)	3.437*** (df = 4; 278)	1.770 (df = 4; 264)
<hr/>					

Note:
 *p<0.1; **p<0.05; ***p<0.01
 > stargazer(model11.5,model11.6,model11.7,model11.8,model11.9,
 + type = "text")

Dependent variable:					
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
discovery	-4.342 (6.816)	-0.354 (6.804)	5.535 (6.898)	9.348 (6.722)	6.141 (7.130)
WGI_rq	-0.488 (4.113)	0.243 (4.212)	1.376 (4.355)	5.413 (4.367)	1.833 (4.745)
pre_dis10	15.488*** (5.714)	12.408** (5.852)	10.764* (6.128)	4.202 (6.224)	1.245 (6.953)
discovery:WGI_rq	-9.875 (7.113)	-4.421 (7.066)	2.217 (7.126)	9.960 (6.897)	5.972 (7.196)

	288	273	258	243	228
R2	0.032	0.019	0.016	0.024	0.006
Adjusted R2	-0.111	-0.131	-0.139	-0.135	-0.163
F Statistic	2.090* (df = 4; 250)	1.142 (df = 4; 236)	0.928 (df = 4; 222)	1.283 (df = 4; 208)	0.291 (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4,					
+ type = "text")					
<hr/>					
Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
<hr/>					
discovery	7.801 (8.639)	10.873 (8.239)	12.600 (8.031)	7.924 (7.902)	5.486 (8.002)
GSD_rl_pe	-19.258** (7.979)	-15.002* (7.742)	-12.209 (7.708)	-11.140 (7.772)	-9.132 (8.088)
pre_dis10	7.416* (3.809)	16.206*** (3.752)	22.173*** (3.798)	23.507*** (3.753)	22.074*** (3.820)
discovery:GSD_rl_pe	-50.455** (20.803)	-49.787** (19.793)	-37.729* (19.239)	-21.415 (18.900)	2.189 (19.110)
<hr/>					
Observations	483	468	453	438	423
R2	0.053	0.075	0.092	0.101	0.090
Adjusted R2	-0.057	-0.034	-0.016	-0.007	-0.022
F Statistic	5.993*** (df = 4; 432)	8.427*** (df = 4; 418)	10.224*** (df = 4; 404)	10.983*** (df = 4; 390)	9.266*** (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9,					
+ type = "text")					
<hr/>					
Dependent variable:					
--	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)
--					
discovery	0.966 (7.990)	-1.120 (7.982)	-0.725 (7.925)	-2.577 (7.913)	-4.170 (8.153)
GSD_rl_pe	-5.131 (8.318)	0.388 (8.577)	10.420 (8.806)	15.772* (9.151)	16.459* (9.735)
pre_dis10	23.302*** (3.838)	24.394*** (3.863)	26.074*** (3.870)	25.687*** (3.909)	22.490*** (4.042)
discovery:GSD_rl_pe	23.099 (19.048)	27.710 (18.997)	22.925 (18.824)	31.931* (18.751)	39.956** (19.076)
<hr/>					
--					
Observations	408	393	378	363	348
R2	0.109	0.120	0.133	0.142	0.123
Adjusted R2	-0.002	0.009	0.022	0.029	0.006
F Statistic	11.083*** (df = 4; 362)	11.878*** (df = 4; 348)	12.854*** (df = 4; 334)	13.196*** (df = 4; 320)	10.768*** (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4,					
+ type = "text")					
<hr/>					
Dependent variable:					
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)
--					
discovery	4.952 (9.718)	7.676 (9.282)	23.783*** (8.980)	19.394** (8.809)	28.066*** (8.836)
VD_nl	0.386 (6.918)	3.518 (6.706)	5.281 (6.606)	6.188 (6.655)	9.137 (6.875)

pre_dis10	7.899** (3.939)	16.817*** (3.893)	24.926*** (3.919)	26.020*** (3.870)	25.722*** (3.909)					
discovery:VD_r1	-98.729* (53.794)	-94.679* (51.367)	-155.791*** (49.659)	-120.826** (48.762)	-136.280*** (48.966)					
<hr/>										
Observations	483	468	453	438	423					
R2	0.030	0.057	0.098	0.108	0.109					
Adjusted R2	-0.082	-0.054	-0.009	0.001	-0.0002					
F Statistic	3.362** (df = 4; 432)	6.302*** (df = 4; 418)	11.024*** (df = 4; 404)	11.812*** (df = 4; 390)	11.476*** (df = 4; 376)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)					
<hr/>										
discovery	33.484*** (8.765)	22.528** (8.798)	11.611 (8.728)	10.690 (8.699)	21.009** (8.798)					
VD_r1	11.576* (6.997)	13.862* (7.123)	17.067** (7.183)	20.533*** (7.292)	23.067*** (7.558)					
pre_dis10	27.857*** (3.908)	27.273*** (3.957)	26.790*** (3.963)	25.799*** (3.993)	23.925*** (4.085)					
discovery:VD_r1	-150.076*** (48.630)	-83.945* (48.872)	-23.365 (48.550)	-7.714 (48.462)	-63.776 (48.861)					
<hr/>										
Observations	408	393	378	363	348					
R2	0.134	0.131	0.140	0.145	0.130					
Adjusted R2	0.026	0.021	0.029	0.032	0.013					
F Statistic	13.981*** (df = 4; 362)	13.123*** (df = 4; 348)	13.561*** (df = 4; 334)	13.517*** (df = 4; 320)	11.434*** (df = 4; 306)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)					
<hr/>										
discovery	89.158* (49.475)	81.835 (50.731)	61.676 (50.685)	31.783 (50.932)	-6.682 (51.012)					
EFW	2.212 (2.261)	2.991 (2.414)	4.103* (2.480)	5.931** (2.606)	7.933*** (2.688)					
pre_dis10	6.999 (4.429)	12.044** (4.848)	12.424** (5.272)	12.195** (5.476)	8.220 (5.713)					
discovery:EFW	-19.882** (8.662)	-17.918** (8.877)	-13.837 (8.864)	-7.560 (8.903)	0.300 (8.912)					
<hr/>										
Observations	304	294	281	268	255					
R2	0.139	0.120	0.103	0.077	0.058					
Adjusted R2	0.012	-0.015	-0.038	-0.072	-0.097					
F Statistic	10.636*** (df = 4; 264)	8.664*** (df = 4; 254)	6.964*** (df = 4; 242)	4.774*** (df = 4; 230)	3.378** (df = 4; 218)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)					
<hr/>										
discovery	-52.755 (51.453)	-58.163 (51.529)	-114.066** (51.921)	-117.267** (50.879)	-132.105** (56.267)					
EFW	5.734**	5.251*	4.976*	4.199	2.907					

	(2.782)	(2.867)	(2.930)	(2.926)	(3.047)					
pre_dis10	9.342 (6.065)	8.587 (6.493)	4.714 (7.166)	1.009 (8.015)	-2.969 (10.353)					
discovery:IEF	8.816 (8.985)	10.481 (8.993)	20.952** (9.055)	21.835** (8.868)	24.245** (9.929)					
<hr/>										
Observations	242	229	216	203	190					
R2	0.045	0.038	0.058	0.064	0.054					
Adjusted R2	-0.117	-0.131	-0.113	-0.112	-0.132					
F Statistic	2.435** (df = 4; 206)	1.914 (df = 4; 194)	2.778** (df = 4; 182)	2.898** (df = 4; 170)	2.247* (df = 4; 158)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)					
<hr/>										
discovery	76.039 (53.195)	68.319 (53.117)	105.584** (52.890)	47.842 (52.691)	21.950 (52.073)					
IEF	0.291 (0.207)	0.382* (0.209)	0.414* (0.212)	0.441** (0.216)	0.355 (0.218)					
pre_dis10	-5.086 (4.387)	4.720 (4.690)	11.221** (5.088)	12.445** (5.176)	9.677* (5.244)					
discovery:IEF	-1.798* (1.051)	-1.558 (1.049)	-2.180** (1.044)	-1.004 (1.040)	-0.417 (1.028)					
<hr/>										
Observations	378	364	350	336	322					
R2	0.051	0.041	0.045	0.039	0.021					
Adjusted R2	-0.078	-0.091	-0.089	-0.099	-0.123					
F Statistic	4.443*** (df = 4; 332)	3.394*** (df = 4; 319)	3.640*** (df = 4; 306)	2.985** (df = 4; 293)	1.486 (df = 4; 280)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)					
<hr/>										
discovery	7.243 (50.114)	-9.385 (49.739)	-45.670 (50.271)	-79.342 (50.530)	-77.535 (51.118)					
IEF	0.422** (0.213)	0.362* (0.217)	0.340 (0.224)	0.310 (0.230)	0.342 (0.237)					
pre_dis10	10.606** (5.192)	9.910* (5.332)	7.648 (5.619)	2.888 (5.952)	-3.503 (6.462)					
discovery:IEF	-0.068 (0.989)	0.292 (0.982)	1.022 (0.992)	1.653* (0.997)	1.587 (1.011)					
<hr/>										
Observations	308	294	280	266	252					
R2	0.028	0.025	0.025	0.023	0.025					
Adjusted R2	-0.117	-0.124	-0.129	-0.135	-0.139					
F Statistic	1.944 (df = 4; 267)	1.655 (df = 4; 254)	1.522 (df = 4; 241)	1.367 (df = 4; 228)	1.350 (df = 4; 215)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)					
<hr/>										
discovery	-92.204*** (22.050)	-85.674*** (22.089)	-85.853*** (21.926)	-69.749*** (21.828)	-55.720** (21.891)					

CBIE	-41.738*** (10.160)	-37.398*** (10.288)	-36.079*** (10.337)	-33.714*** (10.531)	-35.481*** (10.833)					
pre_dis10	4.193 (4.310)	14.644*** (4.535)	24.218*** (4.784)	26.357*** (4.814)	24.387*** (4.886)					
discovery:CBIE	140.506*** (38.806)	135.590*** (38.914)	148.118*** (38.686)	123.277*** (38.492)	108.194*** (38.578)					
Observations	387	374	361	348	335					
R2	0.087	0.087	0.111	0.114	0.101					
Adjusted R2	-0.042	-0.045	-0.019	-0.018	-0.035					
F Statistic	8.084*** (df = 4; 338)	7.773*** (df = 4; 326)	9.851*** (df = 4; 314)	9.704*** (df = 4; 302)	8.161*** (df = 4; 290)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)					
discovery	-44.946** (21.695)	-8.785 (21.315)	-1.374 (20.646)	-7.289 (20.406)	-8.206 (20.139)					
CBIE	-40.415*** (10.923)	-48.550*** (11.045)	-59.828*** (10.993)	-67.342*** (11.220)	-70.317*** (11.495)					
pre_dis10	23.751*** (4.892)	24.179*** (4.907)	26.899*** (4.846)	25.949*** (4.900)	17.041*** (4.989)					
discovery:CBIE	92.757** (38.056)	27.300 (37.524)	12.259 (36.328)	23.429 (35.884)	24.034 (35.433)					
Observations	322	309	296	283	270					
R2	0.109	0.138	0.191	0.201	0.170					
Adjusted R2	-0.029	0.002	0.061	0.069	0.029					
F Statistic	8.484*** (df = 4; 278)	10.627*** (df = 4; 266)	15.016*** (df = 4; 254)	15.244*** (df = 4; 242)	11.781*** (df = 4; 230)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap (1)	FE_cap1 (2)	FE_cap2 (3)	FE_cap3 (4)	FE_cap4 (5)					
discovery	42.123 (26.352)	48.235* (25.583)	43.866* (24.934)	3.681 (24.538)	-14.146 (24.761)					
EcGI	-0.649*** (0.127)	-0.469*** (0.126)	-0.340*** (0.126)	-0.284** (0.127)	-0.203 (0.131)					
pre_dis10	8.941** (3.683)	16.866*** (3.696)	22.477*** (3.747)	23.886*** (3.715)	22.811*** (3.780)					
discovery:EcGI	-1.006** (0.511)	-1.072** (0.496)	-0.873* (0.483)	-0.062 (0.475)	0.405 (0.480)					
Observations	480	468	453	438	423					
R2	0.090	0.092	0.101	0.104	0.094					
Adjusted R2	-0.014	-0.015	-0.006	-0.004	-0.017					
F Statistic	10.582*** (df = 4; 430)	10.527*** (df = 4; 418)	11.302*** (df = 4; 404)	11.319*** (df = 4; 390)	9.714*** (df = 4; 376)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")										
<hr/>										
Dependent variable:										
	FE_cap5 (1)	FE_cap6 (2)	FE_cap7 (3)	FE_cap8 (4)	FE_cap9 (5)					
discovery	-28.239 (24.646)	-45.550* (24.479)	-52.548** (24.210)	-53.755** (24.175)	-50.386** (24.497)					

EcGI	-0.129 (0.135)	-0.079 (0.138)	-0.062 (0.143)	-0.037 (0.150)	0.078 (0.159)
pre_dis10	24.240*** (3.796)	24.979*** (3.807)	25.890*** (3.807)	25.185*** (3.846)	21.613*** (3.958)
discovery:EcGI	0.741 (0.477)	1.072** (0.474)	1.185** (0.468)	1.237*** (0.467)	1.195** (0.473)
<hr/>					
Observations	408	393	378	363	348
R2	0.113	0.128	0.141	0.142	0.119
Adjusted R2	0.002	0.017	0.031	0.029	0.001
F Statistic	11.485*** (df = 4; 362)	12.745*** (df = 4; 348)	13.734*** (df = 4; 334)	13.250*** (df = 4; 320)	10.339*** (df = 4; 306)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				

2.5. RE per capita

Dependent variable:					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	1.607 (3.576)	1.401 (3.554)	1.623 (3.585)	1.387 (3.570)	2.129 (3.559)
WGI	0.145 (0.189)	0.166 (0.195)	0.203 (0.201)	0.233 (0.203)	0.224 (0.207)
pre_dis10	2.094** (1.027)	1.453 (1.098)	0.667 (1.221)	0.544 (1.238)	0.204 (1.259)
discovery:WGI	-0.098 (0.661)	-0.091 (0.658)	0.011 (0.666)	0.042 (0.662)	0.202 (0.660)
<hr/>					
Observations	360	348	333	318	303
R2	0.024	0.016	0.011	0.009	0.009
Adjusted R2	-0.102	-0.116	-0.125	-0.130	-0.134
F Statistic	1.946 (df = 4; 318)	1.243 (df = 4; 306)	0.809 (df = 4; 292)	0.648 (df = 4; 278)	0.589 (df = 4; 264)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					
<hr/>					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	2.093 (3.458)	2.268 (3.428)	2.314 (3.354)	1.789 (3.317)	1.394 (3.268)
WGI	0.222 (0.206)	0.184 (0.210)	0.173 (0.213)	0.113 (0.219)	0.167 (0.225)
pre_dis10	-0.199 (1.254)	-0.488 (1.281)	-0.941 (1.301)	-1.640 (1.351)	-2.270 (1.408)
discovery:WGI	0.208 (0.640)	0.297 (0.634)	0.404 (0.619)	0.386 (0.612)	0.362 (0.599)
<hr/>					
Observations	288	273	258	243	228
R2	0.009	0.007	0.007	0.009	0.016
Adjusted R2	-0.137	-0.144	-0.149	-0.153	-0.151
F Statistic	0.591 (df = 4; 250)	0.438 (df = 4; 236)	0.415 (df = 4; 222)	0.477 (df = 4; 208)	0.802 (df = 4; 194)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")					
<hr/>					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)

discovery	2.027 (5.257)	2.377 (5.489)	2.449 (5.799)	3.434 (6.128)	3.607 (6.312)					
SFI	0.009 (0.112)	-0.023 (0.117)	-0.022 (0.124)	0.019 (0.131)	0.061 (0.135)					
pre_dis10	-0.009 (0.975)	-0.019 (1.018)	-0.129 (1.075)	-0.177 (1.136)	-0.289 (1.170)					
discovery:SFI	-0.065 (0.348)	-0.088 (0.364)	-0.101 (0.384)	-0.181 (0.406)	-0.188 (0.418)					
<hr/>										
Observations	360	360	360	360	360					
R2	0.006	0.006	0.005	0.003	0.004					
Adjusted R2	-0.122	-0.122	-0.124	-0.125	-0.124					
F Statistic (df = 4; 318)	0.469	0.459	0.367	0.272	0.359					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)					
<hr/>										
discovery	3.044 (6.238)	3.481 (6.122)	3.150 (6.042)	2.419 (5.902)	2.675 (5.742)					
SFI	0.135 (0.137)	0.199 (0.142)	0.243* (0.146)	0.323** (0.149)	0.450*** (0.153)					
pre_dis10	-0.696 (1.177)	-0.898 (1.179)	-1.222 (1.191)	-1.740 (1.196)	-2.098* (1.201)					
discovery:SFI	-0.159 (0.413)	-0.204 (0.405)	-0.211 (0.400)	-0.186 (0.390)	-0.222 (0.380)					
<hr/>										
Observations	348	333	318	303	288					
R2	0.008	0.012	0.016	0.029	0.050					
Adjusted R2	-0.125	-0.123	-0.122	-0.111	-0.090					
F Statistic	0.602 (df = 4; 306)	0.890 (df = 4; 292)	1.151 (df = 4; 278)	1.938 (df = 4; 264)	3.306** (df = 4; 250)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)					
<hr/>										
discovery	1.442 (1.727)	1.655 (1.698)	1.797 (1.660)	1.274 (1.607)	1.390 (1.574)					
CSCI	0.436 (0.298)	0.350 (0.296)	0.309 (0.293)	0.347 (0.287)	0.297 (0.285)					
pre_dis10	0.479 (0.971)	-0.158 (0.995)	-0.883 (1.023)	-0.950 (0.996)	-1.144 (0.981)					
discovery:CSCI	0.307 (1.654)	0.721 (1.634)	1.224 (1.608)	1.009 (1.555)	1.196 (1.521)					
<hr/>										
Observations	469	454	439	424	409					
R2	0.009	0.007	0.008	0.009	0.009					
Adjusted R2	-0.109	-0.113	-0.114	-0.115	-0.117					
F Statistic	0.964 (df = 4; 418)	0.734 (df = 4; 404)	0.831 (df = 4; 390)	0.820 (df = 4; 376)	0.854 (df = 4; 362)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")										
<hr/>										
Dependent variable:										
<hr/>										
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)					

	RE_cap	RE_cap1	RE_cap2	RE_cap3	RE_cap4
	(1)	(2)	(3)	(4)	(5)
discovery	1.824 (3.954)	0.696 (3.911)	-0.409 (3.844)	-0.477 (3.709)	-1.215 (3.628)
GSD_rl	22.387*** (3.430)	22.046*** (3.476)	22.332*** (3.500)	22.752*** (3.465)	22.578*** (3.454)
pre_dis10	0.361 (0.910)	-0.300 (0.932)	-0.977 (0.953)	-1.106 (0.925)	-1.306 (0.911)
discovery:GSD_rl	-2.439 (12.402)	0.788 (12.259)	3.512 (12.036)	2.658 (11.619)	4.971 (11.369)
Observations	483	468	453	438	423
R2	0.093	0.091	0.096	0.103	0.107
Adjusted R2	-0.011	-0.016	-0.011	-0.005	-0.002
F Statistic	11.130*** (df = 4; 432)	10.461*** (df = 4; 418)	10.720*** (df = 4; 404)	11.240*** (df = 4; 390)	11.310*** (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
	RE_cap5	RE_cap6	RE_cap7	RE_cap8	RE_cap9
	(1)	(2)	(3)	(4)	(5)
discovery	-1.067 (3.574)	-1.898 (3.497)	-2.873 (3.443)	-3.040 (3.397)	-2.944 (3.339)
GSD_rl	23.759*** (3.462)	26.149*** (3.449)	28.167*** (3.477)	29.166*** (3.514)	29.100*** (3.533)
pre_dis10	-1.538* (0.905)	-1.809** (0.893)	-2.102** (0.887)	-2.398*** (0.885)	-2.621*** (0.881)
discovery:GSD_rl	3.976 (11.207)	5.954 (10.971)	7.762 (10.806)	7.485 (10.670)	6.525 (10.510)
Observations	408	393	378	363	348
R2	0.122	0.150	0.176	0.193	0.201
Adjusted R2	0.013	0.043	0.070	0.087	0.094
F Statistic	12.548*** (df = 4; 362)	15.412*** (df = 4; 348)	17.826*** (df = 4; 334)	19.123*** (df = 4; 320)	19.291*** (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4, + type = "text")					
	RE_cap	RE_cap1	RE_cap2	RE_cap3	RE_cap4

	(1)	(2)	(3)	(4)	(5)
discovery	0.242 (1.630)	0.170 (1.659)	0.053 (1.694)	0.093 (1.718)	-0.049 (1.741)
PLTV_xconst	-0.424** (0.200)	-0.403** (0.204)	-0.444** (0.208)	-0.539** (0.211)	-0.604*** (0.214)
pre_dis10	-0.894 (0.843)	-0.901 (0.859)	-0.950 (0.877)	-1.024 (0.889)	-1.127 (0.901)
discovery:PLTV_xconst	0.133 (0.525)	0.186 (0.534)	0.209 (0.545)	0.119 (0.553)	0.208 (0.560)
Observations	420	420	420	420	420
R2	0.016	0.015	0.016	0.021	0.025
Adjusted R2	-0.102	-0.104	-0.102	-0.097	-0.092
F Statistic (df = 4; 374)	1.531	1.411	1.555	2.002*	2.444**
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")					
Dependent variable:					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	0.160 (1.735)	-0.103 (1.732)	-0.643 (1.736)	-0.774 (1.733)	-1.136 (1.714)
PLTV_xconst	-0.532** (0.216)	-0.450** (0.218)	-0.382* (0.221)	-0.316 (0.224)	-0.280 (0.225)
pre_dis10	-1.381 (0.904)	-1.599* (0.910)	-1.852** (0.920)	-2.166** (0.928)	-2.437*** (0.929)
discovery:PLTV_xconst	0.051 (0.560)	0.054 (0.560)	0.089 (0.563)	0.025 (0.563)	0.109 (0.560)
Observations	408	393	378	363	348
R2	0.023	0.020	0.020	0.023	0.027
Adjusted R2	-0.098	-0.103	-0.106	-0.106	-0.104
F Statistic	2.133* (df = 4; 362)	1.816 (df = 4; 348)	1.705 (df = 4; 334)	1.844 (df = 4; 320)	2.092* (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4, + type = "text")					
Dependent variable:					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	1.743 (2.251)	1.389 (2.237)	1.218 (2.255)	0.543 (2.255)	0.780 (2.258)
WGI_ge	-0.390 (0.859)	-0.132 (0.877)	0.254 (0.904)	0.459 (0.916)	0.597 (0.938)
pre_dis10	2.037** (1.024)	1.439 (1.092)	0.708 (1.205)	0.641 (1.221)	0.350 (1.243)
discovery:WGI_ge	-0.459 (2.590)	-0.627 (2.574)	-0.494 (2.597)	-0.878 (2.591)	-0.467 (2.588)
Observations	360	348	333	318	303
R2	0.023	0.014	0.008	0.006	0.005
Adjusted R2	-0.103	-0.118	-0.128	-0.134	-0.138
F Statistic	1.860 (df = 4; 318)	1.081 (df = 4; 306)	0.576 (df = 4; 292)	0.393 (df = 4; 278)	0.359 (df = 4; 264)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9, + type = "text")					
Dependent variable:					

	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	0.733 (2.205)	0.668 (2.198)	0.591 (2.163)	0.035 (2.151)	-0.266 (2.286)
WGI_ge	0.731 (0.928)	0.755 (0.940)	0.864 (0.948)	0.956 (0.979)	1.402 (0.998)
pre_dis10	-0.044 (1.238)	-0.321 (1.265)	-0.783 (1.285)	-1.504 (1.335)	-2.212 (1.391)
discovery:WGI_ge	-0.439 (2.520)	-0.142 (2.503)	0.419 (2.453)	0.276 (2.428)	0.263 (2.523)
Observations	288	273	258	243	228
R2	0.007	0.006	0.006	0.010	0.022
Adjusted R2	-0.140	-0.146	-0.150	-0.151	-0.145
F Statistic	0.411 (df = 4; 250)	0.334 (df = 4; 236)	0.350 (df = 4; 222)	0.550 (df = 4; 208)	1.068 (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4, + type = "text")					
Dependent variable:					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	0.169 (4.740)	0.022 (4.704)	0.013 (4.728)	-0.683 (4.695)	0.313 (4.682)
WGI_rl	3.206*** (0.980)	3.204*** (1.004)	3.255*** (1.026)	3.561*** (1.035)	3.510*** (1.045)
pre_dis10	2.241** (1.000)	1.620 (1.067)	0.918 (1.180)	0.803 (1.192)	0.478 (1.213)
discovery:WGI_rl	-1.956 (4.207)	-1.902 (4.175)	-1.658 (4.199)	-1.952 (4.166)	-0.971 (4.150)
Observations	360	348	333	318	303
R2	0.054	0.046	0.041	0.046	0.045
Adjusted R2	-0.068	-0.082	-0.091	-0.088	-0.093
F Statistic	4.561*** (df = 4; 318)	3.671*** (df = 4; 306)	3.108** (df = 4; 292)	3.319** (df = 4; 278)	3.088** (df = 4; 264)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9, + type = "text")					
Dependent variable:					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	0.439 (4.536)	0.448 (4.487)	0.508 (4.360)	-0.225 (4.301)	-0.243 (4.486)
WGI_rl	3.637*** (1.032)	3.751*** (1.048)	4.193*** (1.059)	4.308*** (1.077)	4.699*** (1.071)
pre_dis10	0.044 (1.205)	-0.268 (1.229)	-0.752 (1.240)	-1.584 (1.284)	-2.355* (1.327)
discovery:WGI_rl	-0.806 (4.017)	-0.552 (3.970)	-0.082 (3.853)	-0.347 (3.796)	-0.091 (3.908)
Observations	288	273	258	243	228
R2	0.051	0.054	0.068	0.077	0.100
Adjusted R2	-0.089	-0.090	-0.079	-0.074	-0.053
F Statistic	3.374** (df = 4; 250)	3.379** (df = 4; 236)	4.045*** (df = 4; 222)	4.315*** (df = 4; 208)	5.415*** (df = 4; 194)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4, + type = "text")					
Dependent variable:					

	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	2.192 (1.524)	1.917 (1.513)	1.670 (1.523)	1.215 (1.521)	1.353 (1.520)
WGI_rq	-0.253 (0.771)	-0.074 (0.812)	0.133 (0.852)	0.513 (0.869)	0.386 (0.892)
pre_dis10	2.054** (1.021)	1.416 (1.090)	0.648 (1.209)	0.580 (1.226)	0.267 (1.247)
discovery:WGI_rq	0.056 (1.600)	0.043 (1.590)	0.155 (1.604)	0.083 (1.598)	0.402 (1.592)

=====
Observations 360 348 333 318 303
R2 0.022 0.014 0.008 0.006 0.005
Adjusted R2 -0.184 -0.118 -0.128 -0.134 -0.138
F Statistic 1.819 (df = 4; 318) 1.059 (df = 4; 306) 0.560 (df = 4; 292) 0.404 (df = 4; 278) 0.326 (df = 4; 264)
=====

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9,
+ type = "text")

	Dependent variable:				
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	1.253 (1.482)	1.116 (1.475)	0.852 (1.449)	0.428 (1.435)	0.200 (1.420)
WGI_rq	0.298 (0.894)	-0.130 (0.913)	-0.663 (0.915)	-1.384 (0.932)	-1.681* (0.945)
pre_dis10	-0.121 (1.243)	-0.404 (1.268)	-0.860 (1.287)	-1.562 (1.329)	-2.180 (1.385)
discovery:WGI_rq	0.350 (1.547)	0.566 (1.531)	0.943 (1.496)	1.002 (1.473)	1.051 (1.433)

=====
Observations 288 273 258 243 228
R2 0.005 0.003 0.006 0.017 0.028
Adjusted R2 -0.142 -0.149 -0.151 -0.144 -0.137
F Statistic 0.301 (df = 4; 250) 0.207 (df = 4; 236) 0.319 (df = 4; 222) 0.905 (df = 4; 208) 1.393 (df = 4; 194)
=====

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4,
+ type = "text")

	Dependent variable:				
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	-0.072 (2.050)	-0.347 (2.005)	-0.850 (1.948)	-1.608 (1.873)	-1.529 (1.843)
GSD_rl_pe	-8.687*** (1.893)	-9.585*** (1.884)	-10.465*** (1.870)	-11.583*** (1.843)	-11.442*** (1.862)
pre_dis10	0.306 (0.904)	-0.331 (0.913)	-1.066 (0.921)	-1.334 (0.890)	-1.540* (0.880)
discovery:GSD_rl_pe	4.552 (4.937)	4.878 (4.816)	5.427 (4.667)	6.503 (4.481)	6.088 (4.400)

=====
Observations 483 468 453 438 423
R2 0.050 0.062 0.076 0.096 0.096
Adjusted R2 -0.059 -0.048 -0.034 -0.013 -0.015
F Statistic 5.736*** (df = 4; 432) 6.859*** (df = 4; 418) 8.309*** (df = 4; 404) 10.341*** (df = 4; 390) 9.984*** (df = 4; 376)
=====

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9,
+ type = "text")

Dependent variable:					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	-2.152 (1.823)	-2.503 (1.801)	-2.829 (1.802)	-3.194* (1.801)	-3.114* (1.822)
GSD_rl_pe	-12.221*** (1.898)	-13.324*** (1.936)	-13.706*** (2.003)	-13.916*** (2.083)	-13.402*** (2.176)
pre_dis10	-1.965** (0.876)	-2.359*** (0.872)	-2.748*** (0.880)	-3.247*** (0.890)	-3.647*** (0.904)
discovery:GSD_rl_pe	7.256* (4.346)	7.530* (4.287)	7.162* (4.281)	7.282* (4.268)	6.250 (4.264)
Observations	408	393	378	363	348
R2	0.110	0.128	0.134	0.138	0.130
Adjusted R2	-0.001	0.018	0.022	0.025	0.014
F Statistic	11.161*** (df = 4; 362)	12.827*** (df = 4; 348)	12.912*** (df = 4; 334)	12.832*** (df = 4; 320)	11.474*** (df = 4; 306)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4, + type = "text")					
Dependent variable:					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	0.925 (2.334)	0.259 (2.304)	-0.508 (2.268)	-0.572 (2.200)	-0.905 (2.156)
VD_rl	-0.693 (1.661)	-0.768 (1.665)	-0.646 (1.668)	-0.079 (1.662)	-0.059 (1.677)
pre_dis10	0.437 (0.946)	-0.214 (0.967)	-0.945 (0.990)	-1.037 (0.966)	-1.231 (0.954)
discovery:VD_rl	2.602 (12.919)	5.761 (12.752)	8.688 (12.541)	6.878 (12.177)	8.603 (11.948)
Observations	483	468	453	438	423
R2	0.004	0.004	0.006	0.004	0.006
Adjusted R2	-0.111	-0.112	-0.113	-0.116	-0.116
F Statistic	0.488 (df = 4; 432)	0.447 (df = 4; 418)	0.566 (df = 4; 404)	0.431 (df = 4; 390)	0.568 (df = 4; 376)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text")					
Dependent variable:					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	-0.772 (2.142)	-1.349 (2.129)	-2.185 (2.125)	-2.465 (2.113)	-2.533 (2.087)
VD_rl	0.289 (1.710)	0.778 (1.724)	1.141 (1.748)	1.594 (1.772)	1.973 (1.791)
pre_dis10	-1.458 (0.955)	-1.737* (0.957)	-2.055** (0.965)	-2.381** (0.970)	-2.634*** (0.969)
discovery:VD_rl	6.580 (11.882)	8.626 (11.826)	11.066 (11.818)	11.039 (11.774)	10.493 (11.590)
Observations	408	393	378	363	348
R2	0.007	0.010	0.015	0.022	0.028
Adjusted R2	-0.116	-0.115	-0.112	-0.107	-0.102

F Statistic 0.670 (df = 4; 362) 0.918 (df = 4; 348) 1.280 (df = 4; 334) 1.767 (df = 4; 320) 2.227* (df = 4; 306)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4,
+           type = "text")
```

Dependent variable:

	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	-1.854 (12.761)	-2.212 (12.740)	-1.593 (12.811)	-1.982 (12.751)	-0.857 (12.692)
EFW	-4.245*** (0.583)	-3.969*** (0.606)	-3.644*** (0.627)	-3.482*** (0.653)	-3.208*** (0.669)
pre_dis10	3.303*** (1.142)	2.819** (1.217)	2.449* (1.333)	2.390* (1.371)	2.219 (1.421)
discovery:EFW	0.665 (2.234)	0.718 (2.229)	0.580 (2.240)	0.588 (2.229)	0.402 (2.217)

Observations 304 294 281 268 255
R2 0.202 0.174 0.147 0.130 0.115
Adjusted R2 0.084 0.047 0.013 -0.010 -0.032

F Statistic 16.692*** (df = 4; 264) 13.347*** (df = 4; 254) 10.392*** (df = 4; 242) 8.613*** (df = 4; 230) 7.052*** (df = 4; 218)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9,
+           type = "text")
```

Dependent variable:

	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
discovery	-2.867 (12.715)	-3.625 (12.533)	-3.484 (12.132)	-6.464 (11.504)	-8.668 (11.918)
EFW	-2.802*** (0.687)	-2.433*** (0.697)	-2.136*** (0.685)	-2.126*** (0.662)	-1.765*** (0.645)
pre_dis10	1.800 (1.499)	1.613 (1.579)	1.391 (1.674)	0.621 (1.812)	0.079 (2.193)
discovery:EFW	0.755 (2.220)	0.876 (2.187)	0.791 (2.116)	1.246 (2.005)	1.617 (2.103)

Observations 242 229 216 203 190
R2 0.090 0.072 0.059 0.061 0.049
Adjusted R2 -0.065 -0.091 -0.111 -0.116 -0.138

F Statistic 5.091*** (df = 4; 206) 3.755*** (df = 4; 194) 2.874** (df = 4; 182) 2.748** (df = 4; 170) 2.014* (df = 4; 158)

Note:

*p<0.1; **p<0.05; ***p<0.01

```
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4,
+           type = "text")
```

Dependent variable:

	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
discovery	2.095 (11.919)	1.817 (11.768)	1.811 (11.804)	1.816 (11.834)	0.442 (11.736)
IEF	-0.195*** (0.046)	-0.218*** (0.046)	-0.211*** (0.047)	-0.205*** (0.049)	-0.195*** (0.049)
pre_dis10	2.010** (0.983)	1.170 (1.039)	0.388 (1.136)	0.277 (1.163)	0.086 (1.182)
discovery:IEF	-0.010 (0.235)	-0.010 (0.232)	-0.017 (0.233)	-0.024 (0.234)	0.002 (0.232)

Observations 378 364 350 336 322
R2 0.073 0.079 0.068 0.061 0.057

Adjusted R2	-0.052	-0.049	-0.063	-0.074	-0.081
F Statistic	6.575*** (df = 4; 332)	6.795*** (df = 4; 319)	5.587*** (df = 4; 306)	4.747*** (df = 4; 293)	4.208*** (df = 4; 280)
<hr/>					
Note: > stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")					
<hr/>					
Dependent variable:					
<hr/>					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
<hr/>					
discovery	0.188 (11.577)	0.133 (11.418)	-0.495 (11.123)	-0.724 (10.780)	-1.377 (10.569)
IEF	-0.186*** (0.049)	-0.181*** (0.050)	-0.197*** (0.049)	-0.203*** (0.049)	-0.194*** (0.049)
pre_dis10	-0.212 (1.199)	-0.431 (1.224)	-0.853 (1.243)	-1.580 (1.270)	-2.055 (1.336)
discovery:IEF	0.005 (0.229)	0.001 (0.225)	0.002 (0.220)	-0.003 (0.213)	0.007 (0.209)
<hr/>					
Observations	308	294	280	266	252
R2	0.053	0.052	0.064	0.076	0.079
Adjusted R2	-0.088	-0.094	-0.084	-0.074	-0.075
F Statistic	3.766*** (df = 4; 267)	3.459*** (df = 4; 254)	4.097*** (df = 4; 241)	4.669*** (df = 4; 228)	4.615*** (df = 4; 215)
<hr/>					
Note: > stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")					
<hr/>					
Dependent variable:					
<hr/>					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
<hr/>					
discovery	4.217 (5.482)	5.623 (5.352)	7.023 (5.258)	7.118 (5.198)	7.573 (5.174)
CBIE	2.391 (2.526)	2.807 (2.493)	3.169 (2.479)	3.412 (2.508)	3.359 (2.560)
pre_dis10	0.573 (1.072)	-0.267 (1.099)	-1.275 (1.147)	-1.590 (1.147)	-1.969* (1.155)
discovery:CBIE	-4.689 (9.648)	-7.606 (9.429)	-10.744 (9.278)	-11.581 (9.167)	-12.635 (9.118)
<hr/>					
Observations	387	374	361	348	335
R2	0.010	0.010	0.013	0.014	0.017
Adjusted R2	-0.131	-0.133	-0.131	-0.133	-0.132
F Statistic	0.831 (df = 4; 338)	0.786 (df = 4; 326)	1.047 (df = 4; 314)	1.094 (df = 4; 302)	1.276 (df = 4; 290)
<hr/>					
Note: > stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")					
<hr/>					
Dependent variable:					
<hr/>					
	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
<hr/>					
discovery	7.263 (5.138)	8.167 (5.085)	8.306 (5.045)	6.694 (4.935)	5.282 (4.794)
CBIE	2.793 (2.597)	2.542 (2.635)	1.922 (2.686)	0.704 (2.713)	0.058 (2.737)
pre_dis10	-2.427** (1.163)	-2.887** (1.171)	-3.391*** (1.184)	-3.918*** (1.185)	-4.321*** (1.188)
discovery:CBIE	-12.466 (9.049)	-14.747 (8.952)	-16.063* (8.877)	-14.060 (8.678)	-12.067 (8.435)
<hr/>					
Observations	322	309	296	283	270

R2	0.020	0.027	0.035	0.046	0.059
Adjusted R2	-0.131	-0.127	-0.121	-0.111	-0.101
F Statistic	1.443 (df = 4; 278)	1.814 (df = 4; 266)	2.291* (df = 4; 254)	2.944** (df = 4; 242)	3.588*** (df = 4; 230)
<hr/>					
Note: > stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
<hr/>					
Dependent variable:					
	RE_cap (1)	RE_cap1 (2)	RE_cap2 (3)	RE_cap3 (4)	RE_cap4 (5)
<hr/>					
discovery	4.849 (6.591)	5.638 (6.456)	4.560 (6.294)	3.115 (6.104)	2.731 (5.979)
EcGI	0.041 (0.032)	0.045 (0.032)	0.042 (0.032)	0.038 (0.032)	0.044 (0.032)
pre_dis10	0.359 (0.921)	-0.196 (0.933)	-0.804 (0.946)	-0.946 (0.924)	-1.131 (0.913)
discovery:EcGI	-0.071 (0.128)	-0.090 (0.125)	-0.074 (0.122)	-0.052 (0.118)	-0.046 (0.116)
<hr/>					
Observations	480	468	453	438	423
R2	0.008	0.009	0.009	0.008	0.010
Adjusted R2	-0.105	-0.107	-0.109	-0.112	-0.111
F Statistic	0.914 (df = 4; 430)	0.946 (df = 4; 418)	0.924 (df = 4; 404)	0.746 (df = 4; 390)	0.951 (df = 4; 376)
<hr/>					
Note: > stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
<hr/>					

	RE_cap5 (1)	RE_cap6 (2)	RE_cap7 (3)	RE_cap8 (4)	RE_cap9 (5)
<hr/>					
discovery	0.329 (5.929)	0.714 (5.891)	1.165 (5.880)	2.056 (5.854)	2.742 (5.768)
EcGI	0.054* (0.032)	0.061* (0.033)	0.065* (0.035)	0.061* (0.036)	0.060 (0.037)
pre_dis10	-1.461 (0.913)	-1.713* (0.916)	-1.987** (0.925)	-2.291** (0.931)	-2.555*** (0.932)
discovery:EcGI	-0.003 (0.115)	-0.015 (0.114)	-0.033 (0.114)	-0.056 (0.113)	-0.072 (0.111)
<hr/>					
Observations	408	393	378	363	348
R2	0.014	0.018	0.021	0.025	0.031
Adjusted R2	-0.109	-0.107	-0.105	-0.103	-0.099
F Statistic	1.283 (df = 4; 362)	1.564 (df = 4; 348)	1.826 (df = 4; 334)	2.073* (df = 4; 320)	2.414** (df = 4; 306)
<hr/>					
Note: *p<0.1; **p<0.05; ***p<0.01					

3. Energy efficiency

	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
<hr/>					
discovery	71.946*** (24.752)	59.871** (24.708)	53.319** (24.493)	42.866* (24.392)	28.616 (24.307)
WGI	5.037*** (1.387)	4.119*** (1.409)	3.255** (1.426)	2.187 (1.457)	1.874 (1.493)
pre_dis10	-12.002 (8.444)	-11.961 (8.583)	-4.873 (8.690)	-5.444 (8.874)	-1.383 (9.116)
discovery:WGI	9.877** (4.601)	8.306* (4.590)	7.759* (4.547)	6.108 (4.524)	4.173 (4.505)

Observations	334	319	304	289	274
R2	0.093	0.068	0.045	0.028	0.015
Adjusted R2	-0.031	-0.062	-0.092	-0.115	-0.135
F Statistic	7.485*** (df = 4; 293)	5.104*** (df = 4; 279)	3.116** (df = 4; 265)	1.824 (df = 4; 251)	0.908 (df = 4; 237)

Note:
> stargazer(model4.5,model4.6,model4.7,model4.8,model4.9,
+ type = "text")

Dependent variable:					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	20.067 (24.413)	5.735 (24.127)	-8.741 (23.238)	-9.284 (23.182)	-6.016 (21.634)
WGI	1.379 (1.554)	0.963 (1.592)	0.101 (1.614)	-0.544 (1.665)	-0.216 (1.605)
pre_dis10	-3.887 (9.506)	2.405 (9.862)	6.819 (10.147)	8.854 (9.974)	4.095 (9.261)
discovery:WGI	3.436 (4.528)	0.801 (4.463)	-1.276 (4.298)	-2.201 (4.250)	-0.289 (3.956)

Observations	259	244	229	214	199
R2	0.008	0.003	0.004	0.006	0.006
Adjusted R2	-0.148	-0.160	-0.165	-0.170	-0.179
F Statistic	0.428 (df = 4; 223)	0.136 (df = 4; 209)	0.192 (df = 4; 195)	0.254 (df = 4; 181)	0.233 (df = 4; 167)

Note:
> stargazer(model5.0,model5.1,model5.2,model5.3,model5.4,
+ type = "text")

Dependent variable:					
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	-50.469 (39.789)	-58.088 (39.975)	-63.622 (40.765)	-69.193* (41.579)	-74.900* (41.880)
SFI	8.442*** (0.849)	7.657*** (0.852)	6.518*** (0.869)	5.561*** (0.916)	4.775*** (0.970)
pre_dis10	-19.117** (7.379)	-19.850*** (7.413)	-14.780* (7.560)	-15.362* (7.847)	-13.431* (8.062)
discovery:SFI	4.046 (2.637)	4.365 (2.649)	4.538* (2.701)	4.823* (2.753)	4.942* (2.771)

Observations	360	360	360	349	334
R2	0.264	0.228	0.170	0.128	0.095
Adjusted R2	0.169	0.129	0.063	0.012	-0.028
F Statistic	28.450*** (df = 4; 318)	23.501*** (df = 4; 318)	16.239*** (df = 4; 318)	11.266*** (df = 4; 307)	7.722*** (df = 4; 293)

Note:
> stargazer(model5.5,model5.6,model5.7,model5.8,model5.9,
+ type = "text")

Dependent variable:					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	-85.319** (42.241)	-82.780* (42.209)	-37.438 (41.735)	23.595 (40.822)	-3.257 (39.491)
SFI	3.620*** (1.019)	2.715** (1.064)	1.216 (1.110)	0.329 (1.130)	-1.268 (1.150)
pre_dis10	-14.868* (8.324)	-14.507* (8.551)	-9.864 (8.751)	-5.097 (8.588)	-2.407 (8.360)
discovery:SFI	5.289* (2.793)	5.013* (2.787)	1.931 (2.753)	-1.774 (2.700)	-0.233 (2.614)

	319	304	289	274	259					
Observations	319	304	289	274	259					
R2	0.066	0.047	0.015	0.005	0.011					
Adjusted R2	-0.064	-0.090	-0.130	-0.146	-0.145					
F Statistic	4.956*** (df = 4; 279)	3.275** (df = 4; 265)	0.970 (df = 4; 251)	0.324 (df = 4; 237)	0.592 (df = 4; 223)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model6.0,model6.1,model6.2,model6.3,model6.4, + type = "text")										
=====										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
discovery	23.415* (12.485)	24.098* (12.308)	22.124* (12.040)	17.718 (11.698)	13.853 (11.514)					
CSCI	5.078** (2.209)	3.499 (2.203)	1.788 (2.183)	0.239 (2.150)	-1.222 (2.157)					
pre_dis10	-24.863*** (7.716)	-27.476*** (7.648)	-25.850*** (7.527)	-26.402*** (7.363)	-25.963*** (7.301)					
discovery:CSCI	17.028 (12.115)	22.221* (11.929)	25.025** (11.656)	22.661** (11.311)	22.750** (11.117)					
=====										
Observations	440	425	410	395	380					
R2	0.052	0.049	0.040	0.038	0.038					
Adjusted R2	-0.065	-0.069	-0.082	-0.085	-0.088					
F Statistic	5.308*** (df = 4; 391)	4.867*** (df = 4; 377)	3.745*** (df = 4; 363)	3.492*** (df = 4; 349)	3.336** (df = 4; 335)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model6.5,model6.6,model6.7,model6.8,model6.9, + type = "text")										
=====										
Dependent variable:										
	GDP_TES5 (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)					
discovery	10.202 (11.275)	5.494 (11.036)	-1.183 (10.821)	-2.700 (10.715)	2.873 (10.555)					
CSCI	-3.531 (2.154)	-5.535** (2.158)	-7.740*** (2.172)	-9.390*** (2.193)	-11.060*** (2.226)					
pre_dis10	-28.057*** (7.209)	-27.758*** (7.124)	-27.568*** (7.056)	-27.052*** (6.950)	-27.289*** (6.863)					
discovery:CSCI	24.067** (10.870)	19.946* (10.622)	13.729 (10.377)	5.557 (10.184)	17.164* (10.014)					
=====										
Observations	365	350	335	320	305					
R2	0.053	0.063	0.083	0.101	0.124					
Adjusted R2	-0.074	-0.065	-0.046	-0.027	-0.005					
F Statistic	4.457*** (df = 4; 321)	5.185*** (df = 4; 307)	6.590*** (df = 4; 293)	7.867*** (df = 4; 279)	9.356*** (df = 4; 265)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model7.0,model7.1,model7.2,model7.3,model7.4, + type = "text")										
=====										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
discovery	-53.044* (29.972)	-51.332* (29.427)	-55.962* (28.694)	-46.889* (27.802)	-44.964 (27.370)					
GSD_rl	78.167*** (27.247)	77.244*** (27.478)	70.740*** (27.311)	63.944** (26.897)	54.157** (26.954)					
pre_dis10	-27.821*** (7.431)	-28.343*** (7.343)	-25.574*** (7.210)	-25.093*** (7.040)	-23.544*** (6.990)					
discovery:GSD_rl	202.093**	184.774**	185.570**	148.558*	129.578					

	(93.806)	(92.135)	(89.870)	(87.115)	(85.800)
<hr/>					
Observations	454	439	424	409	394
R2	0.062	0.061	0.053	0.050	0.043
Adjusted R2	-0.049	-0.052	-0.063	-0.068	-0.078
F Statistic	6.730*** (df = 4; 405)	6.374*** (df = 4; 391)	5.225*** (df = 4; 377)	4.736*** (df = 4; 363)	3.918*** (df = 4; 349)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9,					
+ type = "text")					
<hr/>					
Dependent variable:					
<hr/>					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	-45.089* (26.914)	-26.548 (26.465)	-10.492 (26.035)	0.860 (25.710)	-20.773 (25.535)
GSD_r1	37.013 (27.128)	20.427 (27.273)	-3.326 (27.441)	-19.800 (27.724)	-35.771 (28.229)
pre_dis10	-24.076*** (6.939)	-22.279*** (6.897)	-21.216*** (6.873)	-21.774*** (6.823)	-20.365*** (6.818)
discovery:GSD_r1	114.455 (84.415)	50.272 (83.053)	-6.311 (81.746)	-26.654 (80.980)	30.576 (80.552)
<hr/>					
Observations	379	364	349	334	319
R2	0.042	0.037	0.039	0.042	0.043
Adjusted R2	-0.081	-0.089	-0.090	-0.089	-0.091
F Statistic	3.690*** (df = 4; 335)	3.079** (df = 4; 321)	3.077** (df = 4; 307)	3.224** (df = 4; 293)	3.103** (df = 4; 279)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.0,model18.1,model18.2,model18.3,model18.4,					
+ type = "text")					
<hr/>					
Dependent variable:					
<hr/>					
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	10.213 (13.873)	7.782 (13.605)	-1.038 (13.264)	-6.883 (12.948)	-14.828 (12.727)
PLTV_xconst	-0.109 (1.704)	-0.146 (1.671)	-0.640 (1.630)	-0.466 (1.610)	-0.596 (1.600)
pre_dis10	-23.369*** (7.180)	-23.449*** (7.041)	-20.568*** (6.865)	-21.071*** (6.751)	-20.291*** (6.688)
discovery:PLTV_xconst	-1.548 (4.465)	-1.480 (4.379)	0.608 (4.269)	2.427 (4.164)	3.903 (4.101)
<hr/>					
Observations	420	420	420	409	394
R2	0.033	0.032	0.024	0.027	0.027
Adjusted R2	-0.083	-0.084	-0.093	-0.093	-0.095
F Statistic	3.179** (df = 4; 374)	3.131** (df = 4; 374)	2.343* (df = 4; 374)	2.532** (df = 4; 363)	2.467** (df = 4; 349)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9,					
+ type = "text")					
<hr/>					
Dependent variable:					
<hr/>					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	-22.988* (12.482)	-24.220** (12.241)	-22.670* (12.067)	-20.220* (11.892)	-24.195** (11.811)
PLTV_xconst	-0.986 (1.589)	-1.711 (1.580)	-1.943 (1.584)	-2.097 (1.596)	-2.289 (1.617)
pre_dis10	-21.532*** (6.618)	-21.632*** (6.554)	-22.041*** (6.538)	-23.209*** (6.481)	-20.349*** (6.476)

discovery:PLTV_xconst	5.144 (4.031)	5.095 (3.963)	3.959 (3.917)	5.031 (3.891)	5.006 (3.882)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.036	0.041	0.045	0.050	0.047					
Adjusted R2	-0.087	-0.084	-0.082	-0.080	-0.086					
F Statistic	3.157** (df = 4; 335)	3.463*** (df = 4; 321)	3.640*** (df = 4; 307)	3.817*** (df = 4; 293)	3.476*** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4, + type = "text")										
<hr/>										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
<hr/>										
discovery	34.256** (15.586)	26.291* (15.552)	23.988 (15.515)	19.640 (15.478)	15.443 (15.488)					
WGI_ge	23.155*** (6.283)	20.449*** (6.353)	14.874** (6.483)	11.619* (6.560)	8.967 (6.680)					
pre_dis10	-7.428 (8.369)	-8.064 (8.473)	-1.786 (8.599)	-3.086 (8.756)	-0.100 (8.993)					
discovery:WGI_ge	13.601 (18.004)	9.164 (17.927)	12.024 (17.847)	9.511 (17.763)	10.034 (17.723)					
<hr/>										
Observations	334	319	304	289	274					
R2	0.082	0.064	0.036	0.026	0.014					
Adjusted R2	-0.044	-0.067	-0.102	-0.118	-0.136					
F Statistic	6.524*** (df = 4; 293)	4.764*** (df = 4; 279)	2.494** (df = 4; 265)	1.667 (df = 4; 251)	0.851 (df = 4; 237)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model19.5,model19.6,model19.7,model19.8,model19.9, + type = "text")										
<hr/>										
Dependent variable:										
	GDP_TES5 (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)					
<hr/>										
discovery	10.914 (15.639)	6.139 (15.563)	-6.918 (15.278)	4.261 (16.244)	1.176 (15.194)					
WGI_ge	6.839 (6.918)	2.004 (7.147)	-3.326 (7.201)	-2.974 (7.271)	4.983 (6.914)					
pre_dis10	-3.178 (9.382)	2.349 (9.757)	7.212 (10.047)	7.550 (9.872)	2.608 (9.126)					
discovery:WGI_ge	10.665 (17.834)	5.815 (17.673)	-6.057 (17.155)	2.668 (17.935)	6.879 (16.675)					
<hr/>										
Observations	259	244	229	214	199					
R2	0.008	0.002	0.006	0.004	0.010					
Adjusted R2	-0.148	-0.161	-0.163	-0.172	-0.174					
F Statistic	0.445 (df = 4; 223)	0.086 (df = 4; 209)	0.270 (df = 4; 195)	0.191 (df = 4; 181)	0.430 (df = 4; 167)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4, + type = "text")										
<hr/>										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
<hr/>										
discovery	85.593** (33.347)	63.582* (33.280)	57.151* (32.932)	47.530 (32.723)	37.297 (32.473)					
WGI_rl	23.879*** (7.219)	19.639*** (7.341)	16.133** (7.367)	11.684 (7.459)	13.526* (7.597)					
pre_dis10	-8.572 (8.338)	-8.906 (8.471)	-2.145 (8.561)	-3.447 (8.723)	-0.196 (8.926)					

discovery:WGI_rl	56.793*	40.751	38.617	31.980	26.465					
(29.648) (29.568) (29.237) (29.029) (28.786)										
Observations	334	319	304	289	274					
R2	0.081	0.057	0.038	0.026	0.021					
Adjusted R2	-0.044	-0.075	-0.100	-0.118	-0.128					
F Statistic	6.459*** (df = 4; 293)	4.232*** (df = 4; 279)	2.589** (df = 4; 265)	1.652 (df = 4; 251)	1.273 (df = 4; 237)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9,										
+ type = "text")										
=====										
Dependent variable:										
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)					
discovery	25.730 (32.551)	12.512 (32.203)	-14.440 (31.442)	7.535 (33.160)	-1.050 (30.905)					
WGI_rl	14.243* (7.912)	12.322 (8.083)	9.111 (8.026)	7.464 (8.089)	5.414 (7.703)					
pre_dis10	-3.071 (9.296)	2.017 (9.663)	6.191 (9.968)	6.711 (9.804)	3.345 (9.092)					
discovery:WGI_rl	20.205 (28.833)	9.075 (28.502)	-11.790 (27.709)	4.365 (28.894)	2.709 (26.867)					
Observations	259	244	229	214	199					
R2	0.018	0.012	0.011	0.008	0.008					
Adjusted R2	-0.136	-0.149	-0.157	-0.167	-0.176					
F Statistic	1.004 (df = 4; 223)	0.644 (df = 4; 209)	0.534 (df = 4; 195)	0.370 (df = 4; 181)	0.354 (df = 4; 167)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4,										
+ type = "text")										
=====										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
discovery	36.394*** (10.536)	29.641*** (10.542)	24.908** (10.446)	21.354** (10.404)	14.631 (10.383)					
WGI_rq	17.743*** (5.901)	13.586** (6.046)	11.797* (6.151)	8.521 (6.299)	8.897 (6.448)					
pre_dis10	-9.774 (8.400)	-10.026 (8.538)	-3.042 (8.617)	-4.184 (8.774)	-0.627 (8.990)					
discovery:WGI_rq	23.618** (11.139)	19.173* (11.119)	17.582 (10.988)	14.962 (10.909)	11.249 (10.842)					
Observations	334	319	304	289	274					
R2	0.082	0.056	0.039	0.027	0.018					
Adjusted R2	-0.044	-0.075	-0.099	-0.116	-0.131					
F Statistic	6.504*** (df = 4; 293)	4.176*** (df = 4; 279)	2.686** (df = 4; 265)	1.771 (df = 4; 251)	1.091 (df = 4; 237)					
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9,										
+ type = "text")										
=====										
Dependent variable:										
	GDP_TESS5 (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)					
discovery	9.630 (10.496)	4.967 (10.434)	-1.519 (10.141)	1.275 (10.114)	-3.929 (9.475)					
WGI_rq	1.820 (6.665)	0.941 (6.784)	-1.318 (6.819)	-3.714 (7.006)	-1.539 (6.781)					
pre_dis10	-3.533	2.266	5.958	7.704	3.721					

	(9.398)	(9.745)	(10.033)	(9.862)	(9.145)					
discovery:WGI_rq	10.764 (10.913)	4.997 (10.786)	1.071 (10.377)	-1.109 (10.248)	0.921 (9.567)					
<hr/>										
Observations	259	244	229	214	199					
R2	0.006	0.002	0.004	0.005	0.006					
Adjusted R2	-0.150	-0.161	-0.165	-0.171	-0.179					
F Statistic	0.333 (df = 4; 223)	0.094 (df = 4; 209)	0.180 (df = 4; 195)	0.228 (df = 4; 181)	0.240 (df = 4; 167)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4, + type = "text")										
<hr/>										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
<hr/>										
discovery	-8.715 (15.111)	-12.830 (14.899)	-13.005 (14.604)	-9.766 (14.177)	-6.937 (13.977)					
GSD_rl_pe	26.146* (14.552)	19.004 (14.709)	13.476 (14.799)	12.389 (14.801)	14.413 (15.059)					
pre_dis10	-23.158*** (7.170)	-24.089*** (7.102)	-21.034*** (6.996)	-21.084*** (6.835)	-19.382*** (6.791)					
discovery:GSD_rl_pe	50.934 (36.260)	52.406 (35.780)	40.611 (34.942)	24.777 (33.871)	5.689 (33.339)					
<hr/>										
Observations	454	439	424	409	394					
R2	0.045	0.042	0.030	0.030	0.028					
Adjusted R2	-0.068	-0.073	-0.088	-0.090	-0.095					
F Statistic	4.806*** (df = 4; 405)	4.299*** (df = 4; 391)	2.930** (df = 4; 377)	2.805** (df = 4; 363)	2.481** (df = 4; 349)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9, + type = "text")										
<hr/>										
Dependent variable:										
	GDP_TES5 (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)					
<hr/>										
discovery	-6.533 (13.750)	-4.255 (13.521)	-5.442 (13.383)	7.052 (13.429)	-1.172 (13.447)					
GSD_rl_pe	13.929 (15.318)	11.880 (15.678)	2.264 (16.191)	0.284 (16.808)	-0.433 (17.742)					
pre_dis10	-19.919*** (6.744)	-19.614*** (6.712)	-20.719*** (6.738)	-21.402*** (6.703)	-18.897*** (6.732)					
discovery:GSD_rl_pe	-8.902 (32.742)	-18.696 (32.129)	-19.061 (31.646)	-38.841 (31.458)	-27.594 (31.465)					
<hr/>										
Observations	379	364	349	334	319					
R2	0.034	0.036	0.040	0.045	0.039					
Adjusted R2	-0.091	-0.090	-0.089	-0.085	-0.095					
F Statistic	2.907** (df = 4; 335)	3.035** (df = 4; 321)	3.167** (df = 4; 307)	3.460*** (df = 4; 293)	2.865** (df = 4; 279)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4, + type = "text")										
<hr/>										
Dependent variable:										
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)					
<hr/>										
discovery	-19.359 (16.908)	-23.319 (16.636)	-29.068* (16.248)	-28.480* (15.747)	-31.942** (15.496)					
VD_rl	33.517*** (12.436)	27.802** (12.566)	20.724 (12.641)	14.427 (12.569)	2.930 (12.542)					

pre_dis10	-26.332*** (7.381)	-27.334*** (7.310)	-24.828*** (7.190)	-24.985*** (7.023)	-24.011*** (6.972)
discovery:VD_r1	178.800* (93.382)	181.483** (91.961)	190.227** (89.904)	172.017** (87.217)	168.811* (85.923)
Observations	454	439	424	409	394
R2	0.057	0.053	0.042	0.040	0.036
Adjusted R2	-0.055	-0.061	-0.075	-0.079	-0.086
F Statistic	6.135*** (df = 4; 405)	5.472*** (df = 4; 391)	4.156*** (df = 4; 377)	3.799*** (df = 4; 363)	3.230** (df = 4; 349)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9, + type = "text")					
Dependent variable:					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	-36.863** (15.174)	-29.151* (14.873)	-21.071 (14.599)	-8.196 (14.354)	-21.535 (14.168)
VD_r1	-10.879 (12.487)	-20.474 (12.466)	-30.006** (12.533)	-36.822*** (12.681)	-43.200*** (12.940)
pre_dis10	-25.148*** (6.893)	-23.814*** (6.830)	-22.930*** (6.785)	-22.807*** (6.709)	-21.331*** (6.669)
discovery:VD_r1	169.032** (84.241)	112.621 (82.677)	52.899 (81.124)	4.452 (79.794)	61.470 (79.034)
Observations	379	364	349	334	319
R2	0.045	0.047	0.057	0.067	0.075
Adjusted R2	-0.078	-0.077	-0.069	-0.060	-0.054
F Statistic	3.904*** (df = 4; 335)	3.981*** (df = 4; 321)	4.655*** (df = 4; 307)	5.252*** (df = 4; 293)	5.682*** (df = 4; 279)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4, + type = "text")					
Dependent variable:					
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	37.335 (95.152)	18.924 (94.410)	28.546 (92.224)	66.618 (90.646)	97.070 (87.870)
EFW	-10.725** (4.652)	-15.056*** (4.811)	-15.854*** (4.846)	-14.673*** (4.875)	-13.809*** (4.856)
pre_dis10	-17.287* (9.906)	-18.318* (10.158)	-10.236 (10.336)	-9.655 (10.694)	-5.039 (11.080)
discovery:EFW	-0.838 (16.645)	1.020 (16.507)	-1.564 (16.117)	-9.029 (15.834)	-15.256 (15.342)
Observations	282	269	256	243	230
R2	0.104	0.102	0.087	0.075	0.064
Adjusted R2	-0.036	-0.042	-0.063	-0.081	-0.099
F Statistic	7.089*** (df = 4; 243)	6.532*** (df = 4; 231)	5.197*** (df = 4; 219)	4.209*** (df = 4; 207)	3.341** (df = 4; 195)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9, + type = "text")					
Dependent variable:					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	141.020* (84.275)	125.310 (82.494)	167.633** (82.243)	139.731 (87.786)	111.424 (85.875)
EFW	-9.116* (4.747)	-10.008** (4.756)	-9.133* (4.776)	-9.790** (4.876)	-6.913 (4.996)

	-7.916 (11.644)	-4.718 (13.015)	4.548 (16.158)	13.517 (16.067)	23.015 (15.596)
discovery:EFW	-24.080 (14.706)	-22.256 (14.390)	-30.463** (14.389)	-25.012 (15.497)	-20.366 (15.152)
<hr/>					
Observations	217	204	191	178	165
R2	0.046	0.046	0.061	0.056	0.055
Adjusted R2	-0.126	-0.133	-0.122	-0.137	-0.149
F Statistic	2.215* (df = 4; 183)	2.047* (df = 4; 171)	2.582** (df = 4; 159)	2.167* (df = 4; 147)	1.947 (df = 4; 135)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4, + type = "text")					
<hr/>					
	Dependent variable:				
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	-282.415*** (80.520)	-219.972*** (79.816)	-176.460** (79.047)	-156.277** (78.229)	-121.041 (77.246)
IEF	1.295*** (0.322)	1.247*** (0.328)	1.229*** (0.330)	1.120*** (0.333)	1.094*** (0.337)
pre_dis10	-1.370 (7.746)	-2.240 (7.841)	2.992 (7.960)	1.537 (8.104)	5.345 (8.279)
discovery:IEF	5.992*** (1.589)	4.649*** (1.576)	3.703** (1.560)	3.239** (1.544)	2.468 (1.525)
<hr/>					
Observations	351	337	323	309	295
R2	0.109	0.085	0.070	0.059	0.052
Adjusted R2	-0.015	-0.046	-0.065	-0.082	-0.093
F Statistic	9.436*** (df = 4; 307)	6.830*** (df = 4; 294)	5.319*** (df = 4; 281)	4.178*** (df = 4; 268)	3.509*** (df = 4; 255)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9, + type = "text")					
<hr/>					
	Dependent variable:				
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TEST7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	-93.681 (76.777)	-52.605 (76.080)	-3.417 (74.557)	41.475 (72.780)	73.310 (69.749)
IEF	0.820** (0.340)	0.636* (0.345)	0.667* (0.346)	0.832** (0.346)	0.662* (0.342)
pre_dis10	4.513 (8.579)	6.850 (8.957)	8.378 (9.421)	6.590 (9.199)	8.344 (8.822)
discovery:IEF	1.812 (1.516)	0.964 (1.502)	-0.035 (1.472)	-0.800 (1.439)	-1.530 (1.379)
<hr/>					
Observations	281	267	253	239	225
R2	0.034	0.025	0.029	0.031	0.035
Adjusted R2	-0.118	-0.133	-0.132	-0.136	-0.138
F Statistic	2.121* (df = 4; 242)	1.460 (df = 4; 229)	1.641 (df = 4; 216)	1.646 (df = 4; 203)	1.725 (df = 4; 190)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4, + type = "text")					
<hr/>					
	Dependent variable:				
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	31.155 (37.967)	40.034 (37.327)	30.769 (36.627)	16.116 (35.816)	-7.420 (35.141)
CBIE	22.995	20.611	16.206	8.340	-2.219

	(17.886)	(17.993)	(18.107)	(18.087)	(18.187)
pre_dis10	-13.525 (8.285)	-15.397* (8.235)	-11.617 (8.177)	-11.957 (8.112)	-9.242 (8.093)
discovery:CBIE	-36.578 (67.002)	-59.673 (65.840)	-50.475 (64.561)	-28.548 (63.105)	5.914 (61.886)
Observations	362	349	336	323	310
R2	0.022	0.019	0.010	0.008	0.006
Adjusted R2	-0.121	-0.126	-0.140	-0.144	-0.150
F Statistic	1.752 (df = 4; 315)	1.488 (df = 4; 303)	0.734 (df = 4; 291)	0.591 (df = 4; 279)	0.410 (df = 4; 267)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9, + type = "text")					
Dependent variable:					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	-25.092 (34.223)	-62.446* (33.216)	-65.408** (32.590)	-56.577* (31.952)	-36.729 (30.593)
CBIE	-10.902 (18.195)	-21.451 (18.232)	-26.745 (18.588)	-25.914 (18.922)	-29.179 (18.934)
pre_dis10	-7.905 (8.036)	-4.005 (7.980)	-4.180 (8.057)	-4.505 (7.958)	1.163 (7.663)
discovery:CBIE	27.594 (60.240)	92.370 (58.436)	95.109* (57.301)	90.456 (56.186)	48.123 (53.740)
Observations	297	284	271	258	245
R2	0.012	0.024	0.031	0.024	0.021
Adjusted R2	-0.147	-0.136	-0.133	-0.146	-0.153
F Statistic	0.787 (df = 4; 255)	1.506 (df = 4; 243)	1.845 (df = 4; 231)	1.319 (df = 4; 219)	1.137 (df = 4; 207)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
Dependent variable:					
	GDP_TES (1)	GDP_TES1 (2)	GDP_TES2 (3)	GDP_TES3 (4)	GDP_TES4 (5)
discovery	-18.974 (45.626)	-11.507 (45.589)	-5.557 (44.933)	1.474 (43.744)	16.117 (43.124)
EcGI	1.357*** (0.230)	1.034*** (0.236)	0.761*** (0.239)	0.508** (0.240)	0.297 (0.244)
pre_dis10	-25.646*** (6.864)	-25.825*** (6.909)	-22.492*** (6.868)	-22.340*** (6.746)	-20.651*** (6.717)
discovery:EcGI	0.515 (0.884)	0.313 (0.884)	0.119 (0.871)	-0.058 (0.847)	-0.417 (0.835)
Observations	454	439	424	409	394
R2	0.110	0.078	0.050	0.038	0.029
Adjusted R2	0.005	-0.033	-0.066	-0.081	-0.093
F Statistic	12.513*** (df = 4; 405)	8.236*** (df = 4; 391)	4.914*** (df = 4; 377)	3.590*** (df = 4; 363)	2.640** (df = 4; 349)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	GDP_TESS (1)	GDP_TES6 (2)	GDP_TES7 (3)	GDP_TES8 (4)	GDP_TES9 (5)
discovery	23.236 (42.315)	35.047 (41.420)	37.906 (40.651)	54.821 (39.898)	49.081 (39.306)

EcGI	0.149 (0.251)	0.006 (0.257)	-0.194 (0.264)	-0.427 (0.271)	-0.753*** (0.278)
pre_dis10	-21.185*** (6.664)	-20.639*** (6.601)	-20.527*** (6.570)	-20.641*** (6.512)	-16.403** (6.473)
discovery:EcGI	-0.648 (0.819)	-0.902 (0.801)	-0.981 (0.786)	-1.206 (0.771)	-1.166 (0.759)
<hr/>					
Observations	379	364	349	334	319
R2	0.034	0.038	0.046	0.058	0.072
Adjusted R2	-0.090	-0.088	-0.082	-0.071	-0.058
F Statistic	2.922** (df = 4; 335)	3.157** (df = 4; 321)	3.667*** (df = 4; 307)	4.474*** (df = 4; 293)	5.399*** (df = 4; 279)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				

4. Investment in renewables

Dependent variable:					
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)
discovery	-43.941 (36.574)	-91.789** (41.594)	-87.605** (40.815)	-75.465* (40.150)	-68.669 (45.416)
PLTV_xconst	-4.355 (8.208)	-4.322 (9.296)	-7.519 (9.003)	-6.471 (8.603)	-15.172 (9.495)
pre_dis10	-68.459*** (26.150)	-92.125*** (28.369)	-67.675*** (26.034)	-58.835** (25.137)	-21.508 (27.979)
discovery:PLTV_xconst	14.950 (11.462)	24.740* (13.247)	22.554* (13.053)	17.548 (12.836)	20.308 (14.512)
<hr/>					
Observations	285	300	315	330	345
R2	0.031	0.047	0.034	0.027	0.015
Adjusted R2	-0.109	-0.087	-0.099	-0.104	-0.115
F Statistic	2.010* (df = 4; 248)	3.243** (df = 4; 262)	2.456** (df = 4; 276)	1.997* (df = 4; 290)	1.123 (df = 4; 304)
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model18.5,model18.6,model18.7,model18.8,model18.9, + type = "text")					
<hr/>					

Dependent variable:					
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)
discovery	40.363 (43.631)	43.358 (42.992)	21.433 (42.912)	-1.209 (42.952)	-76.394* (42.620)
PLTV_xconst	-7.352 (9.483)	-6.547 (7.921)	-3.623 (6.565)	-2.375 (5.825)	-0.812 (5.597)
pre_dis10	-2.446 (27.453)	62.478** (26.138)	50.314** (25.369)	16.313 (24.827)	-0.599 (23.098)
discovery:PLTV_xconst	-8.476 (14.225)	-6.787 (14.032)	0.168 (14.006)	-2.803 (14.011)	17.085 (13.937)
<hr/>					
Observations	345	345	345	345	345
R2	0.006	0.022	0.015	0.003	0.012
Adjusted R2	-0.125	-0.107	-0.115	-0.128	-0.119
F Statistic (df = 4; 304)	0.477	1.700	1.118	0.229	0.887
<hr/>					
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model19.0,model19.1,model19.2,model19.3,model19.4, + type = "text")					
<hr/>					

Dependent variable:					
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)
discovery	31.648	15.846	3.268	-10.968	12.376

	(56.394)	(58.008)	(58.384)	(60.183)	(60.523)
WGI_ge	17.310 (24.468)	29.628 (26.036)	19.772 (24.875)	13.594 (25.916)	11.574 (25.158)
pre_dis10	-63.330** (27.253)	-62.061** (30.525)	-47.440 (31.727)	-54.764 (33.225)	-31.016 (33.304)
discovery:WGI_ge	34.406 (64.802)	27.531 (66.706)	22.479 (67.201)	13.869 (69.084)	32.888 (69.363)
Observations	330	315	315	300	300
R2	0.024	0.024	0.012	0.013	0.005
Adjusted R2	-0.107	-0.111	-0.124	-0.127	-0.135
F Statistic	1.814 (df = 4; 290)	1.667 (df = 4; 276)	0.822 (df = 4; 276)	0.846 (df = 4; 262)	0.347 (df = 4; 262)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model9.5,model9.6,model9.7,model9.8,model9.9, + type = "text")					
<hr/>					
	Dependent variable:				
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)
discovery	3.183 (62.466)	-13.747 (64.359)	24.679 (66.040)	18.205 (70.591)	9.606 (75.516)
WGI_ge	5.966 (26.288)	-16.158 (27.528)	-23.540 (28.990)	-28.207 (32.260)	-23.156 (33.050)
pre_dis10	-13.276 (35.066)	83.896** (37.037)	52.401 (39.250)	19.598 (43.791)	29.091 (45.934)
discovery:WGI_ge	-30.253 (71.388)	-56.374 (73.293)	28.654 (74.903)	29.492 (79.664)	44.376 (83.332)
Observations	285	270	255	240	225
R2	0.006	0.025	0.012	0.005	0.012
Adjusted R2	-0.139	-0.121	-0.140	-0.154	-0.153
F Statistic	0.353 (df = 4; 248)	1.509 (df = 4; 234)	0.687 (df = 4; 220)	0.280 (df = 4; 206)	0.563 (df = 4; 192)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.0,model10.1,model10.2,model10.3,model10.4, + type = "text")					
<hr/>					
	Dependent variable:				
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)
discovery	121.828 (119.937)	39.194 (123.499)	25.466 (124.206)	-12.587 (127.408)	35.546 (127.912)
WGI_rl	6.486 (30.132)	-2.662 (32.362)	-11.521 (29.695)	-14.186 (30.943)	-26.480 (28.575)
pre_dis10	-66.977** (26.805)	-67.807** (30.160)	-50.149 (31.589)	-56.167* (33.065)	-31.755 (33.152)
discovery:WGI_rl	107.548 (106.280)	44.123 (109.451)	38.697 (110.224)	10.478 (112.962)	46.937 (113.390)
Observations	330	315	315	300	300
R2	0.025	0.018	0.010	0.012	0.007
Adjusted R2	-0.106	-0.117	-0.127	-0.127	-0.133
F Statistic	1.851 (df = 4; 290)	1.280 (df = 4; 276)	0.673 (df = 4; 276)	0.809 (df = 4; 262)	0.469 (df = 4; 262)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model10.5,model10.6,model10.7,model10.8,model10.9, + type = "text")					
<hr/>					
	Dependent variable:				
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)

	13.828 (131.450)	-61.885 (134.835)	-2.639 (137.693)	-53.345 (146.303)	-35.991 (154.704)					
WGI_rq	-17.628 (29.921)	-16.882 (31.510)	-5.989 (33.465)	-9.067 (36.664)	-18.112 (36.939)					
pre_dis10	-15.779 (34.923)	82.363** (36.918)	54.386 (39.149)	23.342 (43.674)	32.338 (45.751)					
discovery:WGI_rq	-9.835 (116.413)	-82.938 (119.286)	-5.126 (121.684)	-44.217 (129.139)	-7.624 (134.770)					
<hr/>										
Observations	285	270	255	240	225					
R2	0.006	0.024	0.009	0.002	0.009					
Adjusted R2	-0.138	-0.122	-0.144	-0.157	-0.156					
F Statistic	0.392 (df = 4; 248)	1.424 (df = 4; 234)	0.514 (df = 4; 220)	0.120 (df = 4; 206)	0.456 (df = 4; 192)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.0,model11.1,model11.2,model11.3,model11.4, + type = "text")										
<hr/>										
Dependent variable:										
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)					
<hr/>										
discovery	7.150 (37.575)	-16.924 (38.699)	-19.416 (39.112)	-27.455 (40.519)	-1.594 (40.742)					
WGI_rq	68.218*** (21.507)	72.267*** (23.811)	53.505** (23.864)	24.959 (25.307)	8.772 (23.908)					
pre_dis10	-60.553** (26.433)	-58.953** (29.767)	-44.197 (31.496)	-52.850 (33.207)	-30.904 (33.430)					
discovery:WGI_rq	15.907 (39.102)	-4.128 (40.339)	-0.724 (41.029)	-5.012 (42.362)	18.594 (42.676)					
<hr/>										
Observations	330	315	315	300	300					
R2	0.056	0.050	0.027	0.015	0.005					
Adjusted R2	-0.071	-0.081	-0.107	-0.124	-0.136					
F Statistic	4.292*** (df = 4; 290)	3.596*** (df = 4; 276)	1.889 (df = 4; 276)	1.000 (df = 4; 262)	0.309 (df = 4; 262)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model11.5,model11.6,model11.7,model11.8,model11.9, + type = "text")										
<hr/>										
Dependent variable:										
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)					
<hr/>										
discovery	34.872 (41.956)	18.764 (43.095)	1.255 (44.221)	-1.669 (47.252)	-21.740 (47.062)					
WGI_rq	-3.995 (25.329)	-30.355 (26.692)	-23.183 (27.963)	-27.653 (30.724)	-24.129 (31.345)					
pre_dis10	-17.638 (35.174)	80.980** (37.066)	54.241 (39.284)	20.109 (43.749)	29.694 (45.895)					
discovery:WGI_rq	12.962 (43.783)	-17.759 (44.754)	-2.825 (45.683)	4.404 (48.481)	7.114 (47.501)					
<hr/>										
Observations	285	270	255	240	225					
R2	0.005	0.027	0.012	0.005	0.011					
Adjusted R2	-0.139	-0.118	-0.140	-0.154	-0.154					
F Statistic	0.328 (df = 4; 248)	1.627 (df = 4; 234)	0.686 (df = 4; 220)	0.278 (df = 4; 206)	0.543 (df = 4; 192)					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model12.0,model12.1,model12.2,model12.3,model12.4, + type = "text")										
<hr/>										
Dependent variable:										
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)					

discovery	58.033 (48.386)	41.851 (47.527)	38.152 (47.740)	22.755 (47.839)	20.213 (48.003)					
GSD_rl_pe	63.958 (51.182)	44.056 (50.210)	56.837 (49.740)	32.086 (49.482)	-16.603 (49.801)					
pre_dis10	-67.591*** (26.019)	-56.548** (27.278)	-39.495 (28.322)	-37.711 (28.283)	-16.462 (28.361)					
discovery:GSD_rl_pe	-168.727 (113.209)	-157.016 (112.848)	-163.711 (112.901)	-129.934 (112.892)	-98.715 (113.110)					
Observations	345	345	345	345	345					
R2	0.032	0.023	0.017	0.014	0.006					
Adjusted R2	-0.096	-0.106	-0.112	-0.116	-0.125					
F Statistic (df = 4; 304)	2.491**	1.773	1.338	1.041	0.456					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model12.5,model12.6,model12.7,model12.8,model12.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	SDG_7.a.15	SDG_7.a.16	SDG_7.a.17	SDG_7.a.18	SDG_7.a.19					
	(1)	(2)	(3)	(4)	(5)					
discovery	-24.568 (47.991)	3.388 (47.522)	24.542 (47.563)	-16.859 (47.744)	25.400 (47.916)					
GSD_rl_pe	-23.688 (50.562)	-20.574 (51.344)	-8.671 (52.944)	-14.864 (55.415)	-1.837 (57.512)					
pre_dis10	-9.079 (27.518)	58.372** (26.395)	50.141* (25.644)	14.414 (25.291)	5.060 (23.762)					
discovery:GSD_rl_pe	115.167 (112.370)	59.803 (111.424)	-7.895 (111.618)	23.225 (112.110)	-157.025 (112.120)					
Observations	345	345	345	345	345					
R2	0.006	0.020	0.014	0.003	0.013					
Adjusted R2	-0.125	-0.110	-0.116	-0.129	-0.117					
F Statistic (df = 4; 304)	0.457	1.512	1.048	0.194	1.016					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.0,model13.1,model13.2,model13.3,model13.4,										
+ type = "text")										
<hr/>										
Dependent variable:										
	SDG_7.a.1	SDG_7.a.11	SDG_7.a.12	SDG_7.a.13	SDG_7.a.14					
	(1)	(2)	(3)	(4)	(5)					
discovery	2.823 (62.048)	-59.396 (57.622)	-54.982 (58.691)	-50.059 (58.723)	-54.339 (58.856)					
VD_rl	34.128 (51.373)	30.050 (50.847)	25.924 (51.296)	5.082 (51.329)	-26.747 (51.980)					
pre_dis10	-67.409** (26.594)	-68.128** (28.676)	-49.514 (30.215)	-46.987 (30.231)	-28.912 (30.301)					
discovery:VD_rl	-29.890 (334.772)	272.984 (318.827)	212.139 (324.133)	159.949 (324.251)	233.333 (324.934)					
Observations	345	345	345	345	345					
R2	0.023	0.019	0.010	0.009	0.005					
Adjusted R2	-0.105	-0.110	-0.120	-0.121	-0.126					
F Statistic (df = 4; 304)	1.808	1.474	0.794	0.722	0.393					
<hr/>										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model13.5,model13.6,model13.7,model13.8,model13.9,										
+ type = "text")										
<hr/>										
Dependent variable:										
	SDG_7.a.15	SDG_7.a.16	SDG_7.a.17	SDG_7.a.18	SDG_7.a.19					

	(1)	(2)	(3)	(4)	(5)					
discovery	47.270 (56.339)	51.025 (54.732)	21.431 (54.018)	-18.919 (53.563)	-61.699 (52.000)					
VD_r1	-13.684 (51.250)	-24.638 (48.975)	-15.664 (47.298)	-38.714 (45.465)	-31.748 (44.629)					
pre_dis10	1.874 (30.117)	65.893** (28.266)	49.981* (27.106)	13.638 (26.243)	-3.518 (24.144)					
discovery:VD_r1	-184.074 (316.357)	-161.840 (308.661)	0.499 (305.710)	65.929 (304.020)	178.976 (288.788)					
Observations	345	345	345	345	345					
R2	0.004	0.020	0.014	0.005	0.009					
Adjusted R2	-0.127	-0.109	-0.116	-0.126	-0.121					
F Statistic (df = 4; 304)	0.277	1.552	1.067	0.360	0.727					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.0,model14.1,model14.2,model14.3,model14.4,										
+ type = "text")										
=====										
Dependent variable:										
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)					
discovery	363.858 (292.269)	176.420 (301.334)	299.117 (311.867)	252.589 (317.973)	293.163 (327.421)					
EFW	10.518 (13.447)	5.697 (14.453)	4.160 (15.400)	-5.323 (16.416)	4.545 (17.449)					
pre_dis10	-93.412*** (26.146)	-92.335*** (28.773)	-66.217** (32.413)	-78.303** (34.160)	-66.505* (36.632)					
discovery:EFW	-63.283 (51.155)	-33.905 (52.715)	-56.610 (54.523)	-50.316 (55.562)	-55.989 (57.181)					
Observations	299	286	273	260	247					
R2	0.060	0.046	0.028	0.035	0.025					
Adjusted R2	-0.078	-0.096	-0.121	-0.116	-0.131					
F Statistic	4.134*** (df = 4; 260)	3.005** (df = 4; 248)	1.676 (df = 4; 236)	2.032* (df = 4; 224)	1.357 (df = 4; 212)					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model14.5,model14.6,model14.7,model14.8,model14.9,										
+ type = "text")										
=====										
Dependent variable:										
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)					
discovery	217.019 (334.256)	60.610 (340.491)	297.287 (351.946)	98.474 (368.716)	414.447 (399.785)					
EFW	22.134 (18.102)	35.231* (18.969)	31.182 (19.879)	1.096 (21.224)	-8.530 (21.676)					
pre_dis10	-56.333 (39.402)	91.753** (42.904)	85.294* (48.573)	-16.262 (58.084)	77.388 (73.559)					
discovery:EFW	-35.763 (58.366)	-5.954 (59.424)	-47.845 (61.381)	-20.403 (64.264)	-79.837 (70.546)					
Observations	239	226	213	200	187					
R2	0.021	0.041	0.031	0.002	0.033					
Adjusted R2	-0.142	-0.123	-0.142	-0.182	-0.153					
F Statistic	1.091 (df = 4; 204)	2.075* (df = 4; 192)	1.417 (df = 4; 180)	0.103 (df = 4; 168)	1.319 (df = 4; 156)					
=====										
Note:	*p<0.1; **p<0.05; ***p<0.01									
> stargazer(model15.0,model15.1,model15.2,model15.3,model15.4,										
+ type = "text")										
=====										
Dependent variable:										

	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)
discovery	-302.008 (309.011)	102.668 (301.181)	63.696 (302.492)	145.139 (304.833)	24.795 (307.967)
IEF	2.094 (1.542)	1.383 (1.494)	1.742 (1.432)	0.518 (1.405)	0.269 (1.332)
pre_dis10	-60.978** (26.832)	-55.021* (28.121)	-39.511 (29.122)	-45.621 (29.957)	-30.847 (31.014)
discovery:IEF	6.032 (6.075)	-2.213 (5.949)	-1.561 (5.973)	-3.353 (6.019)	-0.867 (6.080)

Observations	322	322	322	318	314
R2	0.031	0.019	0.013	0.012	0.005
Adjusted R2	-0.103	-0.117	-0.123	-0.127	-0.137
F Statistic	2.264* (df = 4; 282)	1.344 (df = 4; 282)	0.948 (df = 4; 282)	0.838 (df = 4; 278)	0.343 (df = 4; 274)

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model15.5,model15.6,model15.7,model15.8,model15.9,
+ type = "text")

Dependent variable:					
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)
discovery	-160.412 (312.763)	62.954 (318.032)	143.964 (326.274)	178.539 (335.932)	160.153 (342.849)
IEF	0.938 (1.333)	-0.139 (1.390)	0.040 (1.454)	-0.393 (1.531)	-1.251 (1.590)
pre_dis10	-20.397 (32.405)	71.886** (34.094)	65.597* (36.472)	3.539 (39.569)	-33.177 (43.339)
discovery:IEF	3.486 (6.174)	-0.761 (6.278)	-2.400 (6.441)	-3.895 (6.631)	-4.328 (6.778)

Observations	305	291	277	263	249
R2	0.006	0.018	0.014	0.004	0.019
Adjusted R2	-0.140	-0.130	-0.139	-0.155	-0.142
F Statistic	0.422 (df = 4; 265)	1.150 (df = 4; 252)	0.849 (df = 4; 239)	0.205 (df = 4; 226)	1.053 (df = 4; 213)

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model16.0,model16.1,model16.2,model16.3,model16.4,
+ type = "text")

Dependent variable:					
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)
discovery	-60.861 (133.648)	57.792 (131.668)	32.636 (129.930)	23.551 (128.291)	-9.716 (128.408)
CBIE	107.560 (85.773)	163.703* (83.334)	143.424* (77.104)	156.028** (73.185)	105.037 (71.457)
pre_dis10	-64.055** (27.787)	-64.007** (29.184)	-46.675 (30.480)	-47.829 (30.565)	-20.922 (30.926)
discovery:CBIE	113.331 (235.616)	-121.188 (233.752)	-83.665 (230.933)	-69.707 (228.042)	-5.318 (228.154)

Observations	299	298	297	296	295
R2	0.034	0.030	0.022	0.027	0.012
Adjusted R2	-0.107	-0.112	-0.122	-0.117	-0.135
F Statistic	2.275* (df = 4; 260)	2.035* (df = 4; 259)	1.450 (df = 4; 258)	1.750 (df = 4; 257)	0.760 (df = 4; 256)

Note: *p<0.1; **p<0.05; ***p<0.01
> stargazer(model16.5,model16.6,model16.7,model16.8,model16.9,
+ type = "text")

Dependent variable:

	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)
discovery	-95.768 (127.316)	179.548 (124.585)	170.738 (125.990)	156.590 (128.489)	-57.449 (130.854)
CBIE	101.109 (69.495)	107.254 (67.253)	85.967 (68.659)	107.477 (71.264)	101.668 (74.976)
pre_dis10	5.242 (30.527)	55.335* (28.981)	50.110* (29.537)	12.543 (30.832)	8.475 (32.409)
discovery:CBIE	213.253 (224.996)	-266.428 (219.351)	-249.012 (221.741)	-286.881 (225.932)	52.508 (230.217)
Observations	293	290	285	278	267
R2	0.020	0.036	0.030	0.017	0.019
Adjusted R2	-0.127	-0.110	-0.120	-0.139	-0.145
F Statistic	1.297 (df = 4; 254)	2.369* (df = 4; 251)	1.886 (df = 4; 246)	1.042 (df = 4; 239)	1.085 (df = 4; 228)
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.0,model17.1,model17.2,model17.3,model17.4, + type = "text")					
Dependent variable:					
	SDG_7.a.1 (1)	SDG_7.a.11 (2)	SDG_7.a.12 (3)	SDG_7.a.13 (4)	SDG_7.a.14 (5)
discovery	122.124 (253.292)	309.770 (235.274)	285.659 (236.788)	304.816 (236.077)	209.215 (238.812)
EcGI	1.695* (0.997)	1.759* (0.987)	1.955** (0.984)	2.383** (0.971)	1.372 (0.972)
pre_dis10	-75.757*** (26.208)	-64.146** (27.393)	-47.957* (28.460)	-49.105* (28.315)	-24.694 (28.618)
discovery:EcGI	-2.438 (4.762)	-6.230 (4.464)	-5.875 (4.490)	-6.335 (4.476)	-4.342 (4.528)
Observations	345	345	345	345	345
R2	0.031	0.029	0.024	0.031	0.011
Adjusted R2	-0.096	-0.098	-0.105	-0.097	-0.119
F Statistic (df = 4; 304)	2.460**	2.308*	1.844	2.418**	0.828
Note:	*p<0.1; **p<0.05; ***p<0.01				
> stargazer(model17.5,model17.6,model17.7,model17.8,model17.9, + type = "text")					
Dependent variable:					
	SDG_7.a.15 (1)	SDG_7.a.16 (2)	SDG_7.a.17 (3)	SDG_7.a.18 (4)	SDG_7.a.19 (5)
discovery	-305.693 (238.147)	-127.799 (236.569)	66.681 (237.310)	34.402 (238.397)	151.081 (143.677)
EcGI	0.242 (0.958)	-1.012 (0.928)	-0.743 (0.930)	-0.662 (0.939)	-0.145 (0.934)
pre_dis10	-11.889 (27.698)	60.605** (26.283)	52.283** (25.485)	17.969 (24.956)	2.570 (23.215)
discovery:EcGI	6.147 (4.522)	2.946 (4.493)	-0.844 (4.508)	-0.803 (4.529)	-3.599 (2.777)
Observations	345	345	345	345	345
R2	0.009	0.023	0.016	0.004	0.012
Adjusted R2	-0.121	-0.106	-0.114	-0.127	-0.118
F Statistic (df = 4; 304)	0.699	1.767	1.232	0.320	0.950
Note:	*p<0.1; **p<0.05; ***p<0.01				

5. Complete results records of regression models in Chapter 5 Results and Chapter 6 Robustness check

See the spreadsheet:

https://docs.google.com/spreadsheets/d/1vUaRO-N7Ur8yBLzHcFHyv8wMPlxCOTkJ_LsRB109mL8/edit?usp=sharing