Green Investments and Top Income Inequality*

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Abstract

This paper provides empirical evidence for a significant positive association between green investments and top income inequality from a panel of 87 countries from 2004 to 2020. This relationship is strongest for countries with initially lower levels of income, financial development, and carbon emissions. We also find evidence that the effect on inequality persists for four years and thereafter abates. We argue that the positive association between green finance and inequality is at least partially driven by the mechanism of technological change. Using a moderated mediation design, we show that green patents are mediating the relationship between green finance and overall and top income inequality.

Keywords: green finance, income inequality, technological change, innovation, investment emissions, carbon inequality

JEL Classification: D63, E44, O33, Q52, Q54, Q55

1 Introduction

Green investing represents one of the most significant paradigm shifts in financial economics over the past two decades. According to Bloomberg, as of 2022 green investments rose past USD 1.1 trillion for the first time, marking a 31% increase upon 2021 volumes (BloombergNEF, 2023). Yet to go low-carbon, cumulative energy investments alone need to reach USD 48 trillion by 2035 (International Energy Association, 2014). The key role of energy transition investments becomes even more apparent when recognizing that the main contributor to global emissions is the energy sector, accounting for at least 25% of emissions (United States Environmental Protection Agency, 2023). Although there exists evidence that climate change induced inequality

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is further exacerbated by differential abilities to mitigate, adapt, or innovate to protect against climate risks (Avtar, Blickle, Chakrabarti, Janakiraman, & Pinkovskiy, 2021), the literature on the connection between green finance and social welfare topics is scarce at best.

Filling this gap, this paper empirically examines the relationship between energy transition investments and green debt as a proxy for green finance and different measures of inequality in an unbalanced panel dataset covering 87 countries over the years 2004 to 2020. This broad coverage allows us to uncover general effects that hold across the majority of countries as well as heterogeneous effects. We study the direct association between green investments and inequality, and then proceed with analyzing technological change and innovation as a channel. Our empirical approach is based on a two-step system Generalized Method of Moments (SGMM) estimator (Arellano & Bover, 1995; Blundell & Bond, 1998), which is specifically designed to address endogeneity problems, reverse causality, as well as omitted variable bias. To uncover the effect of green investments on inequality, we proceed in two steps.

In the first part of this work, we study the direct effect of green finance on inequality to verify the existence of a relationship between the two concepts. We find that higher amounts of green investments are positively associated with the Gini coefficient as well as with top income inequality, both before and after controlling for numerous country characteristics. This relationship is strongest for countries with initially low levels of financial development and per capita carbon dioxide emissions and low to moderate levels of GDP per capita. Moreover we find a positive significant relationship for non-OECD countries but not for OECD countries. When contrasting green investments to general investments, we find that the main contributor to the increasing effect on inequality is indeed the green investment component. Moreover, we find that the presence of potential greenwashing practices does not alter our findings.

The second part of the paper studies the underlying mechanisms. We postulate that green investments affect inequality mainly through innovation and technological change. Our point of departure revolves around the following hypothesis. Green investments are largely directed towards major technological advances in substitute energy sources and other technologies to reduce or capture carbon emissions. This is inline with the general consensus that innovation is crucial for the transformation to a green economy (see e.g. Aghion, Hepburn, Teytelboym, & Zenghelis, 2014; Aghion, Veugelers, & Hemous, 2009; Hémous, 2021). Such technological change can increase the market power of some firms relative to others, benefiting occupations with close ties to innovation, such as entrepreneurs, scientists, and firm owners, possibly at the cost of lower-skilled workers (Aghion, Akcigit, Bergeaud, Blundell, & Hemous, 2019; Bakija, Cole, & Heim, 2012; Frydman & Papanikolaou, 2018). Moreover, Aghion, Akcigit, Bergeaud, Blundell, and Hemous (2018) show that general innovation is beneficial for the top income earners, increasing their relative income share. Indeed we find evidence for existence of a transmitting effect through innovation and skill-biased technological change that explains the positive association from the first part. In addition to innovation and technological change, we discuss the role of investment emissions in contributing to inequality. While the key purpose of green finance is climate change mitigation, we argue that capital formation associated with large scale green investments[1] leads to higher investment emissions. At least in the short term, green investments potentially contribute to emissions and therefore risk increasing inequality (see i.e. Guivarch, Taconet, & Méjean, 2021; Islam & Winkel, 2017, on the connection of emissions and inequality). Our evidence is important in that it provides first insights into the social effects of a novel and continuously increasing investment paradigm.

The remainder of the paper is organized as follows. We first introduce the related literature in section 2, and continue with the description of the data used in section 3. Section 4 discusses the econometric methodology using the SGMM estimator for dynamic panel models and introduces the basic regression design. The first part of the analysis is provided in section 5, which presents the main results on the association between green investments and inequality. We continue the discussion with the mechanisms in section 6, which introduces the moderated mediation design to determine the presence of a channel, the data used, and presents the results of the mediation analysis. Section 8 concludes.

[1] Examples of large scale green investments include the construction of a find farm, a solar park.

2 Related Literature

Our work relates to at least five strands of literature.

First, we contribute to the recent strand of literature investigating the impact of green and sustainable finance. Carbon pricing is widely viewed as the primary policy approach to address climate change (Stiglitz et al., 2017), but it has recently been shown that it comes at the cost of falling incomes for the poor (Kaenzig, 2023). The focus of the vast majority of works, however, is on environmental outcomes, whereas we are the first to address a social outcome. At the firm level, it has already been established that green bond proceeds positively affect environmental outcomes of firms (Fatica & Panzica, 2021; Flammer, 2021; Mazzacurati, Paris, & Tsiotras, 2021). A few studies also consider the effect of green finance on the regional level in China (Chen & Chen, 2021; Tang, Zhong, Zhang, Dai, & Boamah, 2022; F. Wang, Cai, & Elahi, 2021) and find a negative effect on carbon emissions as well as spillover effects, leading to emission reduction in neighboring areas. At the country level, several studies confirm the results found on the firm and regional level, namely, that green finance reduces CO2 emissions (Fu & Irfan, 2022; M. A. Khan, Riaz, Ahmed, & Saeed, 2022; S. Khan, Akbar, Nasim, Hedvičáková, & Bashir, 2022; Sharif, Saqib, Dong, & Khan, 2022). On the other hand, most recently Bolton, Kacperczyk, and Wiedemann (2022) use global patent filings and corporate financial reporting to establish that, both in the short and in the long term, direct and indirect emissions of firms are not significantly affected by green innovation across all sectors and around the world.

Second, we also relate to the literature on financial development and inequality. There is consensus about the existence of a direct channel of finance to inequality (Beck, Demirgüç-Kunt, & Levine, 2007; Brei, Ferri, & Gambacorta, 2018; Levine, 2008; Tan & Law, 2012), with an accumulating body of empirical results suggesting that financial development benefits individuals in the lower income shares (Beck et al., 2007; Brei et al., 2018; Levine, 2008; Tan & Law, 2012). Extensive reviews on financial development and inequality are given in Claessens and Perotti (2007) and Demirgüç-Kunt and Levine (2009).

Third, our work relates to climate change and inequality. In the poorest economies, a large part of the population, namely the one with the lowest income, directly depends on sectors such as agriculture, forestry, and fishery, which may be most affected by climate change (Guivarch et al., 2021). Indeed, low income groups might face a vicious cycle, whereby initial inequality is reinforced due to the poorer part of the population suffering disproportionately more from adverse effects of climate change (Islam & Winkel, 2017). In addition, the poorer half of the world population contributes only approx. 10% to global emissions, yet the vast majority of that poorer half lives in countries most vulnerable to climate change (Timothy, 2015). Moreover, about 50% of the global emissions are caused by the richest 10% worldwide (Timothy, 2015) and this population group has been unlikely to face adverse effects of climate change, while some even took profit (Callahan & Mankin, 2022).

Fourth, considerable research has been dedicated to investigating the origins of increasing income inequality. General consensus is on two interrelated trends as the primary drivers of recent disparities Schnabel (2021). The first trend pertains to the unequal effects of technological advancements on the income distribution over the past few decades. Technological progress has exhibited a distinct bias towards skilled workers, resulting in a substantial wage growth disparity (Acemoglu, 2002). Second, workers have less power to negotiate for higher wages. Global price competition has made it easier for companies to move jobs to other countries or replace workers with machines, especially for less skilled jobs (Neiman, 2014).

Fifth, our analysis builds on prior work demonstrating the relationship between innovation and inequality. We observe rising within-country income inequality in more than 50% of developed countries and falling income inequality at a high level in over 50% of developing and emerging countries (Cihák & Sahay, 2020), together with a stalling in economic mobility, the ability of the poorer part of the population to improve their economic status, in large parts of the world (The World Bank, 2018). In addition, several prominent studies, including (Aghion et al., 2014, 2009; Hémous, 2021), agree that innovation is key for the transformation to a green economy. However, value creation through innovation mainly benefits the rich (Aghion et al., 2019; Lazonick & Mazzucato, 2013), and risks increasing inequality (Acemoglu, 2002). Indeed, several authors agree that it is the concentration of income at the top that is becoming central to the increase in income inequality (Aghion et al., 2019; Alvaredo, Chancel, Piketty, Saez, &

Zucman, 2018; Alvaredo et al., 2018; Lazonick & Mazzucato, 2013; van Zanden, Baten, Foldvari, & van Leeuwen, 2014). Emerging technologies frequently entail high costs, consequently constraining their initial accessibility to individuals of privileged socioeconomic backgrounds (Roser, Ritchie, & Mathieu, 2023). Empirical work from Aghion et al. (2019) shows for a cross-state US panel a positive and significant association between innovation, measured via patent data, and top income inequality. The authors argue that innovation increases the market power of some firms relative to others, and therefore increase the rents the owners of the advantaged firms earn relative to other firms, possibly at the cost of workers or customers (Autor, Goldin, & Katz, 2020). In addition, Acemoglu (2002) and Goldin and Katz (2007) argue that innovation can increase the returns to some types of skills in the labor market more than others, thus changing relative wages of skilled versus unskilled workers and eventually favoring higher-skilled workers. Connecting innovation with green finance, Aghion et al. (2022) find in a comparison of industries with and without green bond issuance across the EU, that industries with green bond issuance have higher than average innovation. Moreover, two separate studies from China by Zhang, Cheng, and Ma (2022) and T. Wang, Liu, and Wang (2022) empirically link green finance to innovation and find positive associations.

3 Data

Our working sample covers a total of 87 different countries[2] with yearly data from 2004 to 2020, merged in an unbalanced panel dataset. Table 9 displays the variables' summary statistics based on the complete working sample of 87 countries. Descriptive statistics on the connection of green investments to various economic dimensions are in Appendix A.

3.1 Green Investments

Given that green finance is a relatively recent construct and that there are neither perfect nor established measures thereof, our approach is necessarily practical and driven by data availability.

[2] For a complete list see Appendix A. Note that the inclusion of control variables leads to a reduction in sample size.

Green finance is a broad term referring to any form of financial activity that takes into account environmental impact. Such activities typically aim at emission reduction and increasing the resilience against negative climate change impacts (United Nations Framework Convention on Climate Change, 2014). To capture the notion of "green finance" empirically, we use novel, proprietary data from Bloomberg New Energy Finance (BNEF), which track investments and capital spent on deploying low-carbon and renewable energy projects globally. Our indicator of green investments consists of two variables obtained from BNEF, namely energy transition investments (ETI) and green debt proceeds (GD).

ETI track capital spent on deploying low-carbon technologies and capture global investment flows into a range of energy transition sectors in a total of 182 countries. The data is reported at the country level and gives the total amount invested in USD in each sector for each country and year, and includes closed transactions only. Figure 1a shows that the majority of ETI flow into renewable energy, and the investment trend is linearly increasing. Investment in research and development, manufacturing plant, or corporate finance (funds raised by companies to expand) are not included in the dataset. Examples of ETI include infrastructure projects, purchases of electric vehicles, and installations of heat pumps.

GD consists of fixed-income securities on and off the capital markets from a total of 104 countries. We discard social and sustainability linked debt from the dataset and keep green bonds and loans only. All the instruments included are required of having 100% of the raised proceeds earmarked for environmental improvement. GD gives the amount of debt issued in USD and is reported at the issuer level, where issuers can be corporate, municipal, or sovereign. Figure 1b shows that over the period from 2004 to 2020 the majority of green debt stems from the financials, government, utilities and energy industries. Data on the use of proceeds is not disclosed. We allocate green debt according to the country of risk and discard supranational debt. To obtain yearly values, we sum for each country and year the corresponding amounts issued.

Figure 3 displays the total USD amounts of ETI alongside GD over time. Although ETI account for the majority of investment flows, the share of green debt has continued to increase since 2014. Moreover, the number of countries involved in either ETI activities or green debt has also steadily increased.

Green Investment Indicator. To construct our final measure of green investments (GI), we add GD to ETI for each country and year, divide by the corresponding population[3], and finally take the natural logarithm to account for the large differences in per capita issuance amounts. Figure 2 displays GI's quartiles as well as minimum and maximum over the full time horizon, and the number of countries engaging in green investment activity. Clearly, the number of countries doing green investments is steadily increasing, however, there is considerable variability over time. GI has doubled from 2004 to 2020, and is growing approx. linearly, indicating an underlying exponential growth trend. An overview of the coverage and intensity of GI is shown on the world map in Figure 4.

3.2 Inequality

To assess the impact of green finance and inequality, we examine (i) the Gini coefficient ($GINI$), (ii) the income share of the top x percentiles (TOP_x), (iii) the absolute average income of the top x percentiles in natural logarithm (TOP_{xa}), and (iv) the restricted Gini coefficient. We follow Alvaredo (2011) and Aghion et al. (2019) and compute estimates for the restricted Gini coefficient, which considers only the bottom y% of the income distribution. The general formula is $G_y = \frac{GINI - TOP_{(100-y)}}{100 - TOP_{(100-y)}}$, where G_y denotes the restricted Gini coefficient of the bottom y% of the income distribution, $GINI$ is the Gini coefficient over the full distribution, and $TOP_{(100-y)}$ is the income share of the top (100-y)% of the population. We obtain all income measures from the World Inequality Database (WID).[4] The data is standardized, which allows for comparison between countries and over time, and reports pre-tax income, i.e. income before redistributional tax changes. We scale the income shares and the Gini coefficient to the range 0 to 100.

[3]Source: https://data.worldbank.org/indicator/SP.POP.TOTL, as of 22.12.2022.
[4]Source: https://wid.world/, as of 25.05.2023.

3.3 Control variables

Regressing income inequality on green finance raises concerns which can be addressed by adding suitable controls. We thus include a variety of control variables by following, among others, the literature on finance and inequality.

Financial development and income. We control for financial development in our analyses to remove its potential overlap with green finance. We follow the majority of the literature and measure financial development by private credit ($PRIV$), the claims on private sector by deposit money banks as a share of GDP[5] (see e.g. Beck et al., 2007; Brei et al., 2018; Haan & Sturm, 2017; Kim & Lin, 2011). It represents the extent to which new firms have opportunities to obtain bank finance and it therefore is sometimes called financial intermediary development. We include the market capitalization ($MCAP$) of listed domestic companies in USD in percent of GDP as a measure of stock market development (see e.g. Brei et al., 2018; Kim & Lin, 2011). The variable measures the financial market size relative to the size of the economy and thus reflects the importance of financing through equity issuance. The market capitalization data is obtained from Refinitiv, a proprietary data provider, while GDP data is from the World Bank.[6] We include real per capita GDP[7] (GDP) to account for the potential Kuznets curve effect whereby inequality first increases and then decreases with increasing economic output per capita. The idea is rooted in the financial development literature and has a strong empiric history (see e.g. Brei et al., 2018; Clarke, Xu, & Zou, 2006; Kim & Lin, 2011). The original idea was adopted and further developed in the context of sustainability, carbon emissions, and inequality and is called the "environmental Kuznets curve" (see e.g. Ada-Cristina & Lucian-Liviu, 2020; Youssef, Boubaker, & Omri, 2020). We finally include the ratio of government expenditures to GDP (GOV), a common control variable in the finance and inequality literature (see e.g. Haan & Sturm, 2017; Naceur & Zhang, 2016).

[5] Source: `https://data.worldbank.org/indicator/FD.AST.PRVT.GD.ZS`, as of 04.11.2022.
[6] Source: `https://data.worldbank.org/indicator/NY.GDP.MKTP.CD`, as of 29.3.2023.
[7] Source: `https://data.worldbank.org/indicator/NY.GDP.PCAP.CD`, as of 04.11.2022.

Human capital, inflation, and trade. Inflation, secondary school enrollment and trade openness are common control variables in empirical research on the link between finance and inequality (see e.g. Beck et al., 2007; Law, Tan, & Azman-Saini, 2014; Naceur & Zhang, 2016). Secondary school enrollment[8] (SEC) is added to control for the effect of human capital. The earnings premium on education has increased in recent decades in many advanced economies and contributes in large parts to the increase in income inequality (Piketty & Saez, 2014). Human capital can also lead to more technological innovations, which in turn decreases demand for less skilled individuals, which again affects the wage structure (Goldin & Katz, 2007). We include inflation[9] ($INFL$) because price instability could hurt the bottom earners more than the top earners. Higher income households generally have better access to financial instruments which allows them to hedge against inflation risk (Easterly & Fischer, 2001). Furthermore, poorer households tend to hold more cash relative to other financial assets than richer households, which makes poorer households more susceptible to inflation risk (Erosa & Ventura, 2002). We also include trade openness[10] (TRD) to account for the supply of public goods and potential redistributive government expenditures.[11]

Environmental variables. The notion that environmental outcomes can affect inequality is not new in the literature (Ada-Cristina & Lucian-Liviu, 2020; Colmer, 2021; Grigoryev, Makarov, Sokolova, Pavlyushina, & Stepanov, 2020; Islam & Winkel, 2017; Timothy, 2015). The relationship between environmental outcomes and financial development has also been established. Hoepner, Oikonomou, Scholtens, and Schröder (2016) show that there is an economically and statistically significant effect of country sustainability on the cost of bank loans. To address these potential concerns, we control for a country's yearly CO2 emission per capita[12] in natural logarithm ($CO2$) to proxy for country sustainability.

[8]Source: https://data.worldbank.org/indicator/SE.SEC.ENRR, as of 04.11.2022.
[9]Source: https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG, as of 04.11.2022.
[10]Source: https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS, as of 11.10.2022.
[11]For a more detailed analysis and explanation of the mechanisms of trade, finance and inequality, we refer the reader to Kim and Lin (2011).
[12]Source: https://ourworldindata.org/grapher/co-emissions-per-capita, as of 18.01.2023.

4 Econometric Methodology

4.1 SGMM estimator for dynamic panel models

We examine within-country effects in a dynamic panel data model. We aim to address concerns of reversed causality in the relationship between inequality and green investments, leading to potentially biased results if OLS were performed or a static panel approach were used. We thus use a two-step system Generalized Method of Moments (SGMM) estimator that solves the problem of reversed causality and omitted variable bias. The SGMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) is an extension of the difference Generalized Method of Moments estimator of Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991), with their foundation being the Generalized Method of Moments estimator of Hansen (1982). The SGMM estimator is designed for "small T, large N" panels, possibly non strictly exogenous explanatory variables, a dynamic left-hand-side variable that depends on its own past realizations, fixed effects, and heteroskedasticity and autocorrelation within but not across individuals (Roodman, 2009). The problem of non-exogenous variables is addressed by using internal instruments. These are lagged values of the explanatory variables, or differences thereof, that are assumed to be uncorrelated with future values of the error term. While endogenous variables are assumed to be correlated with contemporaneous errors, predetermined, or weakly exogenous, variables are not.[13] The problem of omitted variable bias occurs in cross-sectional regressions in which it is not possible to account for unobserved country-specific effects. They are part of the error term and potentially lead to biased point estimates. Panel models provide a remedy as they remove such unobservables by differencing. The SGMM approach is explained in more detail in Appendix B.

[13] Weak exogeneity implies that future and contemporaneous inequality shocks do not affect contemporaneous green investment, however, it does not imply that anticipated future changes in inequality are not considered in current green investment decisions. In other words, an unpredictable inequality shock in time t will impact green investment in times $t+1, \dots, T$ but not in $t, t-1, \dots, 1$. In contrast, an endogenous variable is affected in time t. Note that the endogeneity and weak exogeneity assumptions are not innocent, they determine the entries in the vector of moments, and therefore determine the parameter estimates.

4.2 Regression Design

We use the following regression equation (1) as the starting model in which the explanatory variable of interest are green investments GI and the outcome variable is an inequality measure $INEQ$. Throughout the analysis we assume that green finance is predetermined.

$$INEQ_{i,t} = \beta_1 GI_{i,t} + \beta_2 INEQ_{i,t-1} + \beta_3 (GI_{i,t} \times INEQ_{i,t-1}) + \beta_4' X_{i,t} + \delta_t + c_i + \epsilon_{i,t}. \quad (1)$$

An individual observation corresponds to a country i in year t. To incorporate the idea that the previous inequality level likely influences the current level[14], we use the lagged value of the inequality indicator as an explanatory variable. Moreover, because in a given year green finance may vary with respect to the preceding year's inequality level, we let green finance interact with the previous year's inequality level. The regression specification includes individual fixed effects c_i, time fixed effects δ_t, an error term $\epsilon_{i,t}$, as well as a set of control variables X. Based on this baseline specification, we introduce the control variables in three steps.

Specification (1.1): We include the logarithm of the average years of secondary school attainment (SEC), the logarithm of the ratio of government spending to GDP (GOV), the annual inflation rate of the consumer price index ($INFL$), the degree of international openness (TRD), and the financial market size relative to the size of the economy ($MCAP$). Based on preceding research on financial development and inequality, we assume that SEC is predetermined.

Specification (1.2): In a second step, we include proxies for country income and financial development. On one hand, economic output may influence income inequality (Baselgia & Foellmi, 2022). On the other hand, the literature agrees that there is a link between financial development and inequality (Beck et al., 2007; Brei et al., 2018; Levine, 2008; Tan & Law, 2012). We therefore control for both per capita GDP (GDP) and private credit ($PRIV$). The literature on growth, financial development and inequality assumes that there is reversed causality in the relationship between inequality and financial development (Claessens & Perotti,

[14]Inequality shows high persistence and we therefore believe that the lagged level is a good predictor of the current level.

2007), and between inequality and economic growth (Acemoglu, Johnson, & Robinson, 2004). We therefore assume that GDP and $PRIV$ are predetermined.

Specification (1.3): In the third and last step, we additionally control for general environmental effects on inequality by including per capita carbon dioxide emissions ($CO2$). Carbon dioxide emissions are a measure of climate change, which has been linked to increases in inequality. We therefore believe that the inclusion of $CO2$ is essential for the validity of our results. We consider the specification (1.3), which includes all covariates, as our baseline model. It serves as the blueprint for the subsequent analyses. Whenever we refer to the baseline model, we refer to equation (1.3).

Specification (1.4): Although the relationship between inequality and green finance is assumed to be linear, it could be possible that different mechanisms dominate at different magnitudes of green investments. This may lead to a nonlinear relationship between green investments and inequality. For example, income inequality might first rise as green investments develop, but later decline as more people benefit from the technological advance generated by green investments and emissions reduction. In the relationship between financial development and inequality, for example, Greenwood and Jovanovic (1990) show how financial and economic development give rise to an inverted U-shaped relationship (see also Clarke et al. (2006)). To explore whether there is an hump shaped relationship between green finance and income inequality, we use a modification of equation (1.3) and incorporate the desired quadratic effect by including $GI^2_{i,t}$.

5 Regression Results

We proceed as follows. First, we show how the association between green investments (GI) and inequality evolves as we add more control variables and test different lags of green finance to understand its long-run effect. Second, we investigate if non-green investments are associated differently to inequality, and address greenwashing concerns by means of an additional, more granular green finance dataset. Third, since we suspect country-level effect heterogeneity, we compute separate effect estimates for different country subsamples. Fifth, we perform robustness checks and thereby analyze additional factors that potentially influence inequality.

5.1 Green finance and inequality

5.1.1 Overall and top income inequality

Table 1 regresses the Gini coefficient (left panel) and the top 5% income share (right panel) on green finance for each specification of equation (1). Adding control variables slightly affects effect strength, however, the coefficient estimate of green investments remains significant and positive throughout. Similarly, the interaction term between green investments and lagged inequality is negative and significant for all specifications, indicating that the effect of GI is attenuated with increasing inequality levels.[15] [16]

Figure 6 visualizes the marginal effect of a 1% change in green investments for each country in the sample against its average lagged $GINI$ or TOP_5 level.[17] We argue that inequality is a slowly changing variable and by taking its average we can meaningfully represent a country with a single data point. Figure 6 indicates that, on overage, we can expect a positive effect on the Gini coefficient and the top 5% income share. The plots also reveal substantial effect differences between countries, with a small number of countries experiencing negative effects. The overall positive effect is confirmed by the computation of the average effect $(\beta_1 + \beta_3\overline{INEQ})$ in the bottom panel of table 1. The average effect represents the mean effect on inequality over all countries and years in the sample for a 1% increase in green investment amounts.

We want to provide two computational examples demonstrating the economic significance of our findings. We start with Norway, which is one of the countries most engaged in green investment activity. Its green investment level was 8.0129 in 2020 while it was 7.6112 in 2019,

[15] The marginal effect of GI is free of GI itself but dependent on the lagged inequality level due to the interaction term.

[16] To ensure that it is indeed top income inequality that is most affected by green investments we run the baseline model for the bottom 20% (0.1078^{***}) and 50% (0.5497^{***}) income shares as well as for the top 50% (4.5246^{***}). Clearly, the upper half of the income distribution responds more strongly.

[17] GI is in natural logarithm and we therefore must consider percentage changes when computing effect strength. The effect on inequality for a $p\%$ change in GI is $\ln((100+p)/100) \times (\beta_1 + \beta_3 INEQ_{i,t-1})$, with β_1 being the coefficient on GI and β_3 being the coefficient on the interaction term between green investments and inequality lagged (see also equation (1)).

corresponding to an increase of 5.28%. Its inequality level in 2020 was 38.91. Assuming that Norway's green investment activity continues to grow at a 5.28% rate from 2020 to 2021, then its inequality level can be expected to rise by 0.02 to 38.93. As a second example we take Mexico, a country with one of the world's highest inequality levels. In 2020, the Gini coefficient was at 74.54. Green investment amounts were 3.8652 in 2019 and 3.4162 in 2020, corresponding to a decrease of 11.62%. Assuming that green investments decrease at the same rate from 2020 to 2021, inequality is expected to increase by 0.03 to 74.57.

Although such number might seem economically small, they become relevant in comparison to the actual changes in the Gini coefficients. The absolute mean first difference in the Gini coefficient over the period 2004 to 2020 was 0.1666 for Mexico and 0.1151 for Norway. An increase of 0.02 in case of Norway is roughly 17% of the mean change, while an increase of 0.03 in case of Mexico is roughly 18% of its mean change. In other words, the observed growth in green investments accounts for approx. a sixth of the observed change in the Gini coefficient.

We continue the discussion of Table 1. The results for specification (1.4) show a significant negative effect of GI squared, indicating a hump-shaped relationship between green investments and the Gini coefficient or the top 5% income share. For $GINI$, the maximum marginal effect of green investments is estimated to lie between approx. 21.415 to 29.015.[18] Given the logarithmic scale of GI, reaching the maximum effect strength requires unrealistic high per capita green investment amounts. Based on a similar argument, the same conclusion is reached for the top 5% income share. Given the actual green investment amounts in the data, we do not further pursue the inverted U-shape analysis.

An important question regarding the association between green finance and inequality is the timing of the effect. If there is a causal mechanism linking green finance and inequality, one would arguably expect the effect to materialize after a period of time rather than immediately. This idea is consistent with the explanatory mechanism we propose in section 6 in terms of innovation. Indeed, Aghion et al. (2019) regress top income inequality on innovation at different

[18] The maximum effect for $GINI$ w.r.t. GI is obtained by solving $2.066 - 0.0723 INEQ_{i,t-1} - 2 \times 0.0723 GI = 0$ for GI and gives the green investment level required to obtain the maximum effect. This effect depends on the lagged Gini coefficient. Based on available inequality data, we set the lower Gini limit to 37.5 and the upper limit to 77.5.

Table 1: The table presents the base regression (1) results for overall inequality ($GINI$) and the top 5% income share (TOP_5) for the subsequent addition of control variables. (1.1) includes SEC, GOV, $INFL$, TRD and $MCAP$. (1.2) additionally includes GDP and $PRIV$. (1.3) additionally includes $CO2$. (1.4) additionally includes GI^2.

	$GINI$				TOP_5			
specification	(1.1)	(1.2)	(1.3)	(1.4)	(1.1)	(1.2)	(1.3)	(1.4)
GI	0.4151**	1.2704***	1.0983***	2.066***	0.8876***	1.0168***	0.8642***	1.4898***
	(0.1925)	(0.1787)	(0.1686)	(0.2729)	(0.1807)	(0.1441)	(0.1291)	(0.2299)
GI^2				-0.0723***				-0.0641***
				(0.0119)				(0.0117)
$GI \times INEQ$ *lagged*	-0.0065**	-0.0214***	-0.0178***	-0.0268***	-0.0217***	-0.0235***	-0.0182***	-0.0241***
	(0.0036)	(0.0033)	(0.0031)	(0.0041)	(0.0055)	(0.0046)	(0.0042)	(0.0058)
control variables	yes	yes	yes	yes	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes
R^2 adj	0.9933	0.9932	0.9928	0.9924	0.9789	0.9791	0.9787	0.978
n total	1644	1562	1562	1562	1644	1562	1562	1562
n unique	87	86	86	86	87	86	86	86
average effect ($\times$100)	0.0582	0.1082	0.1313	0.1219	0.1961	0.2674	0.2847	0.2931
p-val	0.0615	0	0	0.0014	0.0001	0	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *General notes*: see Appendix C. *Table with control variables*: see table 10. *Table-specific notes*: The average effect for the quadratic specification (1.4) is $\ln(1.01) \times (\beta_1 + \beta_3 \overline{INEQ} + 2\beta_5 \overline{GI})$. This is the marginal effect for a 1% change in green investments evaluated at the average lagged inequality and the average green investment level. The standard error for specification (1.4) is computed via $\sqrt{\ln(1.01)^2 \left[\mathrm{VAR}(\beta_1) + \mathrm{VAR}(\beta_3)\overline{INEQ}^2 + 4\mathrm{VAR}(\beta_5)\overline{GI}^2 + 2\overline{INEQ}\mathrm{COV}(\beta_1,\beta_3) + 4\overline{GI}\mathrm{COV}(\beta_1,\beta_5) + 4\overline{GIINEQ}\mathrm{COV}(\beta_3,\beta_5)\right]}$.

lags and find that the effect of innovation on inequality remains significant for up to six years, but that the effect magnitude tapers with higher lags, eventually disappearing. The authors note that their finding is consistent with the view that innovation should have a temporary effect on top income inequality due to imitation and creative destruction. To understand the longer-term effect of green investments, we include a modified version of the baseline model in which we regress inequality on lagged values of green investment. We use the following equation, where the value of the lag is indicated with z:

$$\begin{aligned} INEQ_{i,t} =& \beta_1 GI_{i,t-z} + \beta_2 INEQ_{i,t-1} + \beta_3 (GI_{i,t-z} \times INEQ_{i,t-z-1}) \\ &+ \beta_4 INEQ_{i,t-z-1} + \beta_5 X_{i,t} + \delta_t + c_i + \epsilon_{i,t}. \end{aligned} \tag{2}$$

Note that we have adjusted the interaction term to accommodate the idea that the level of green finance may vary with the lagged level of inequality. Adjusting the interaction term requires to include inequality with lag $z+1$. For $z \geq 1$, we assume $PRIV$, SEC and GDP to be predetermined and $INEQ_{t-1}$ to be endogenous. $INEQ_{t-z-1}$ is then considered an exogenous variable. To reduce output, we present only every second lag in table 2. The results suggest that the association between green investments and inequality remains positive and significant for up to four years, but the effect magnitude decreases after two years. The effect eventually disappears as we increase the lag beyond four years. Interestingly, the average effect turns increasingly negative with increasing lags. Since this paper is an association rather than a causal study, our choice of lag is based on the adjusted R-squared, which tells us not to use lagged green investments. Nevertheless, we want to make a point here that green finance potentially has inequality reduction potential in the long-run. In particular, be believe the following hypothesis to be a plausible explanation for the observed negative average effects. Going back to Aghion et al. (2019)'s finding about the role of innovation, we see that our results are in line with theirs; that is, even if innovation explains the current positive association (see section 6), in the long-run, innovation's increasing effect on inequality fades, and the effect of green investments might start decreasing inequality. In summary, we take our findings as evidence for the existence of a short- to medium-term effect of green investments on inequality, which dampens over the long-run.

Table 2: Results for the time-delayed regression equation (2) for the Gini coefficient ($GINI$) and the top 5% income share (TOP_5). Green finance enters the equation with lag $z \in \{0, 2, 4, 6\}$. Due to space reasons, we provide the output for even lags only.

	GINI				TOP_5			
lag z	0	2	4	6	0	2	4	6
GI lag z	1.0983***	2.0718***	1.3289***	-0.8429**	0.8642***	1.9509***	1.2354***	-0.0562
	(0.1686)	(0.2764)	(0.3439)	(0.4889)	(0.1291)	(0.231)	(0.2721)	(0.2838)
control variables	yes	yes	yes	yes	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes
R^2 adj	0.9928	0.9867	0.9814	0.9774	0.9787	0.958	0.9222	0.9259
n total	1562	1433	1215	987	1562	1433	1215	987
n unique	86	82	78	71	86	82	78	71
average effect (×100)	0.1313	-0.2561	-0.4245	-0.6533	0.2847	-0.3456	-0.3262	-0.7033
p-val	0.4124	0.0228	0.0853	0.1412	0.2655	0.0205	0.0789	0.0162

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *General notes*: see Appendix C.

5.1.2 The role of top incomes

To gain a deeper understanding of the role of top incomes, we compute the effect on (i) top income shares different from the 5% share; (ii) three restricted Gini coefficients, which exclude top shares from the income distribution; and (iii) absolute incomes earned for three different top segments. Based on the regression results of Table 3, we conclude the following.

First, the results on the top 10%, 1% and 0.1% income shares corroborate our main finding that an increase in green investments is associated with an increase in the income share of top earners.

Second, we follow Aghion et al. (2019); Alvaredo (2011); Atkinson and Piketty (2007) and derive an estimate for the Gini coefficient of the bottom 90%, 95%, and 99% of the income distribution, which we denote by G_{90}, G_{95}, and G_{99}, respectively. The results indicate that the positive effect of green investment on income inequality is indeed driven by top income shares: the estimated coefficients on the restricted Gini are very close to zero and roughly 100-200 times smaller than the baseline coefficient. Moreover, the average effect is not significant and becomes positive and relatively large only once higher top income shares are included. We take this as an indication that income inequality is indeed driven by increases of top income shares.

Finally, the last three columns of table 3 show the effect on the average dollar amount earned of the top 10%, 1% and 0.1% of incomes. All top incomes see a positive and significant effect, and the higher the top income, the stronger the effect of green investment becomes. This indicates that relative and absolute top incomes tend to grow when green investment amounts are increased.

5.2 Total investments and greenwashing

Given the nature of our green investment data, the concern of greenwashing and spurious effects of the "green" investment part quickly arise. In particular, the data used is subject to some unobservable categorization scheme that determines if an investment is green or not. Recent research suggests that many investments categorized as green might be falsely labeled (Fletcher & Oliver, 2022). While the data introduced so far gives no direct indication on the credibility

Table 3: The table presents results on the baseline regression (1.3) for the top 10%, 1% and 0.1% income shares, three restricted Gini coefficients, and the average top 10%, 1% and 0.1% of incomes. The restricted Gini coefficient (Gy) based on (Aghion et al., 2019) corresponds to the Gini coefficient computed on the bottom y% of the income distribution.

	top income shares			restricted Gini coefficients			absolute incomes		
	TOP_{10}	TOP_{1}	TOP_{01}	G_{90}	G_{95}	G_{99}	TOP_{10a}	TOP_{1a}	TOP_{01a}
GI	0.6467***	0.4754***	0.0783*	0.0113***	0.0086***	0.0039***	0.5752***	0.918***	1.4619***
	(0.1244)	(0.0914)	(0.0511)	(0.001)	(0.0011)	(0.0013)	(0.0378)	(0.0483)	(0.0668)
$GI \times INEQ$ *lagged*	-0.0092***	-0.0198***	-0.0179**	-0.0642***	-0.0291***	-0.0074***	-0.0482***	-0.0698***	-0.1039***
	(0.0031)	(0.0057)	(0.0086)	(0.0055)	(0.0034)	(0.003)	(0.0033)	(0.0038)	(0.0047)
control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2 adj	0.9888	0.9063	0.554	0.9365	0.984	0.9872	0.9995	0.9992	0.9983
n total	1562	1562	1562	1562	1562	1562	1562	1562	1562
n unique	86	86	86	86	86	86	86	86	86
average effect (×100)	0.2501	0.1756	-0.0103	-0.0017	-0.0012	0.0004	0.0222	0.0317	0.0227
p-val	0	0	0.3268	0	0	0.0559	0	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. ***General notes***: see Appendix C. ***Table with control variables***: see table 11.

of the green labeling, we address above mentioned concerns in two steps. To verify that it is indeed the "green" investment component that drives the positive effects on inequality, we compare the previous results to those of general investments. To weaken greenwashing concerns, we introduce a more granular project-level investment dataset that overlaps with GI but allows discard greenwashing-related investments. We first conduct the analysis based on the general investment data, and then move on to greenwashing concerns.

5.2.1 Total investment effects

We study whether the results found in section 5.1 are specific to green finance or if there is a more general connection between investment flows and inequality. We use a measure of total investments in an economy to analyze the association between total investments and inequality by first regressing inequality on total investments and then simultaneously controlling for green investments (GI). The first regression setup reveals the association between total investments and inequality. By controlling for GI, we then filter out the green component in total investments. If the green investment component indeed drives the effect, we expect the effect of total investments to reduce.

Data. We use annual data on gross fixed capital formation (CFCF) in million US dollars from 2004 to 2020 as a proxy for total investment.[19] The variable's descriptive statistics are given in table 9. CFCF is a macroeconomic aggregate used in national accounting that measures the value of acquisitions of new or existing fixed assets with a life span of more than one year. It includes spending on factories, machinery, equipment, buildings, and infrastructure but excludes the consumption of fixed assets (depreciation) as well as inventories (stocks) or financial investments. To build our indicator of total investments, we compute the natural logarithm of CFCF in USD per capita and denote it as TI. Figure 7 shows total investments in contrast to green finance. The correlation between the two variables is 0.625. Clearly, total investments, although measured in the same unit as green finance, is roughly twice as high on a logarithmic scale with a mean value of 8.582.

Regression approach and hypotheses. We test whether the effect of total investments on inequality reduces in the presence of green investments, thereby implying that the effect on inequality runs partially through the green investment component. Similar to green investments, total investments are assumed to be predetermined, meaning that current investment levels are correlated with shocks to past inequality levels. We run the baseline equation (1.3) in two different specifications. In specification "TI" we replace GI by TI and therefore regress inequality on total investments plus controls; in specification "TI|GI" we use the original setup of equation (1.3) and additionally add TI, hence, we regress inequality on green investments, total investments, and control variables.

Results. Table 4 displays the regression results for both specifications, TI and $TI|GI$, for the Gini coefficient and the top 5% income share. We find strong significant positive associations between total investments and overall as well as top income inequality in specifications "TI". Since total and green investments are measured on the same scale, their coefficients and effect strengths are directly comparable. The coefficients of total investments are roughly four to five times as large as green investments in the baseline regressions, indicating that total investments

[19] Source: https://data.oecd.org/gdp/investment-gfcf.htm#indicator-chart, as of 06.07.2023.

Table 4: The table presents regression results for the baseline equation (1.3) for general investment effects. Specification TI regresses inequality on total investments, specification $TI|GI$ regresses inequality on total investments while controlling for green finance, and specification $TIz|GIz$ is similar to specification $TI|GI$ but uses the approach of standardized regression coefficients. Its advantage over using ordinary coefficients is the possibility to directly compare coefficient sizes.

	$GINI$		TOP_5	
specification	TI	TI|GI	TI	TI|GI
TI	4.8696***	2.4758***	4.7247***	2.4081***
	(0.5198)	(0.5591)	(0.4999)	(0.4564)
GI		-0.3461		-0.8373**
		(0.5613)		(0.3992)
control variables	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes
R^2 adj	0.9612	0.9864	0.8356	0.9665
n total	1507	1217	1507	1217
n unique	56	54	56	54
average effect (×100)	1.1719	1.9795	2.7253	2.8982
p-val	0.0097	0.0008	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *General notes*: see Appendix C. *Table with control variables*: see table 12. *Table-specific notes*: The average effect is computed w.r.t. total investments and not w.r.t. green investment.

are more strongly linked to inequality than green investments. This observation is affirmed by comparing the average effect sizes; the average effects of total investments are approx. nine times as large than for green investments in the baseline regressions. Interestingly, however, in the presence of green investments the coefficients of TI are approximately halved. Green investments therefore have a non-negligible impact on the effect strength of total investments. Regarding the effect of green investments, we argue that the negative (and in the case of the Gini coefficient non-significant) association, is due to two issues: first, the two investment variables are highly correlated, giving rise to potentially inflated coefficients, and second, parts of green investments might be components of total investments, leading to negative coefficients to "filter" out the common components. Overall, the strong reductions in effect sizes of total investments, together with the sign switch of green finance, indicate that part of the effect on inequality runs through the green investment component.

5.2.2 Greenwashing

Greenwashing in the context of investing broadly refers to investments that are incorrectly labeled as green but promoted as such (Flood, 2023; Robeco, 2023; U.S. Bancorp, 2023). A major problem with the green finance indicator GI is its inability to draw conclusions about such greenwashing practices. First, the ETI data reports investments sector-wise with all sectors supposedly belonging to green energy. Second, the GD data reports debt by issuer industry without the option to verify the green label of the debt transaction. Industries themselves are usually a mix of "greener" and "browner" firms, and the dataset does not allow to track a single transaction as it does not provide any details about the individual deals. Common to both GI components is therefore the problem that transactions are not reported at the project level and further information about the "greenness" of the deals is not disclosed. In addition, the higher granularity achievable by analyzing investments at the sector or industry level instead of the currently applicable country level does not help to address greenwashing concerns. Common greenwashing concerns such as incorrect transaction labels, or exploiting minor environmental improvements by means of an aggressive marketing strategy, can therefore not be addressed with our green investment indicator. However, BNEF offers data on renewable energy transactions which are more granular than the Energy Transition Investments and Green Debt datasets, and which allow to filter out potentially questionable transactions. Using this dataset, we can to a certain extent weaken greenwashing concerns.

Data. We work with a project-level dataset from BNEF called renewable energy transactions (RET) for the years 2004 to 2020. The covered energy sectors include solar, wind, biofuels, biomass and waste, geothermal, marine, and hydro, and therefore partially overlap with the sectors covered by ETI. Our main variables in the dataset are the deal value in USD, which reports the transaction amount, and the country, which reports the location of the receiving entity independent of the investors' countries. The dataset distinguishes a transaction to be either of refinancing type, a new investment, or an acquisition. Figure 8 shows the number of deals within each of these categories between 2004 to 2020. Clearly, the majority of RETs are new investments. Each transaction is accompanied by a record that describes the project in more detail including a complete transaction overview with involved entities. For a concrete example, in 2017 a Japanese financial services company as well as one French and two German banks agreed to provide a total of USD 190 million in debt financing for the development of a photovoltaic[20] plant in the USA. The closing date was in 2018. We therefore allocate USD 190 million to the USA in the year 2018.

We build a first indicator of project-level green transactions that encompasses all investment types, and denote it by RET. We sum the deal values for each country and year, divide by the corresponding population and take the natural logarithm. We construct a second indicator of RETs, adjusted to greenwashing concerns. Since refinancing is especially prone to greenwashing practices by relabeling of existing transactions (Chiang, 2023), we exclude transactions characterized as refinancing. We also exclude acquisition transactions. The rationale is that it is unlikely that major new environmental improvements can be obtained from extending a firm's ownership portfolio by the acquisition of a green firm or project. Arguably the only impact such a transaction generates is on the ownership structure, while the green project itself will likely not have a significant change in its environmental impact due to the acquisition. The only category thus left for our analysis is new investments. Although we acknowledge that new investments could also be wrongly labeled as green, we argue that this investment category is the least prone to greenwashing practices. To build the indicator of greenwashing-adjusted RETs, we sum the deal values of new investments for each country and year, divide by the corresponding population and take the natural logarithm. We denote the resulting variable as $RETi$. The relationships of RET and $RETi$ with GI is shown in figures 9a and 9b. The correlation with RET is 0.793 and 0.752 with $RETi$. The variables' descriptive statistics are given in table 9.

Results. To establish the association with inequality we run the baseline equation (1.3) for RET as well as $RETi$. The outcome variables are the Gini coefficient and the top 5% income share. Similar to GI, RET and $RETi$ are assumed to be predetermined. Table 5 reports the regression results. RETs are negatively or slightly positively associated with inequality. The average effects are in the range of the original ones (Table 1) and significant at the 1% level. Greenwashing-adjusted RETs report different coefficient estimates, with the effect on Gini being insignificant and the effect on the top 5% income share being strongly significant but only half

[20] Photovoltaic solar energy is a clean, renewable source of energy that uses solar radiation to produce electricity. It is based on the so-called photoelectric effect, by which certain materials are able to absorb photons (light particles) and release electrons, generating an electric current.

as big as for GI in equation (1.3). However, the average effects are clearly significant and increase when discarding potential non-green transactions. For $RETi$, the average effects are even larger than for GI. Our results indicate that (i) RETs behave similar to green finance in terms of average effects; (ii) RETS are clearly associated with top income inequality; and (iii) greenwashing-adjusted RETs yield stronger average effects than total RETs. We may conclude that qualitatively, greenwashing-adjusted RETs deliver very similar results to green investments. Even if some green investments are labeled wrongly, there seems to be a strong direct association between green finance and top income inequality, and average effects for both the Gini coefficient and the top 5% income share are not greatly disturbed by the practice of greenwashing.

Table 5: The table presents regression results for the baseline equation (1.3) for renewable energy transactions (RETs) to address green washing concerns of the green finance indicator GI. RETs are classified into three investment types: acquisition, refinance, and new investment. The variable RET includes all investment types while the variable $RETi$ adjusts for greenwashing by considering new investments only.

	$GINI$		TOP_5	
RET	-0.4029*** (0.1503)		0.2668* (0.1701)	
$RETi$		0.0275 (0.1692)		0.4646*** (0.1868)
control variables	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes
R^2 adj	0.9955	0.9958	0.97	0.9801
n total	1212	1046	1212	1046
n unique	72	67	72	67
average effect (×100)	0.1404	0.1999	0.2395	0.3165
p-val	0	0	0	0

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ *General notes*: see Appendix C. *Table with control variables*: see table 13. *Table-specific notes*: The average effect is computed w.r.t. renewable energy transactions (RET or $RETi$).

5.3 Effect heterogeneity

In figure 6, we showed that the marginal effect of green investments varies substantially between countries. We now analyze potential sources for explaining the observed effect heterogeneity. Towards this end, we run the baseline equation (1.3) for different country subgroups. We start by dividing the sample into developed and less-developed economies by means of their OECD membership status in each year. For this classification, we use the OECD's List of Member

Countries,[21] which yields 36 OECD and 55 non-OECD countries for our sample.[22] The regression results in Table 6 suggest a striking difference between OECD and non-OECD countries. We find a positive and significant effect of green investments only for non-OECD countries. Moreover, the average effect on the Gini coefficient has doubled, compared to the baseline result. Overall, our results suggest that the effect of green investments on inequality is not driven by developed countries.

Table 6: The table shows the regression results for the baseline equation (1.3) for the subsample of countries in the OECD and the subsample of countries not in the OECD. The outcomes are the Gini coefficient ($GINI$) and the top 5% income share (TOP_5).

	$GINI$		TOP_5	
	OECD	non-OECD	OECD	non-OECD
GI	0.9717	2.536***	0.3049	2.1047***
	(0.9687)	(0.259)	(0.6604)	(0.1799)
$GI \times INEQ$ *lagged*	-0.017	-0.0387***	-0.0053	-0.0513***
	(0.0189)	(0.0044)	(0.023)	(0.0049)
control variables	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes
R^2 adj	0.9914	0.991	0.9716	0.9684
n total	866	674	866	674
n unique	36	55	36	55
average effect (×100)	0.1624	0.2794	0.1655	0.2893
p-val	0.1274	0	0.1141	0
mean $PRIV$	94.5223	57.2485	94.5223	57.2485
mean GDP	38.2883	8.7425	38.2883	8.7425
mean $CO2$	2.0498	0.8411	2.0498	0.8411

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$ *General notes*: see Appendix C. *Table with control variables*: see table 14. *Table-specific notes*: The OECD membership is determined based on the OECD's categorization[21] of countries. Countries that enter the OECD between 2004 and 2020 will be categorized as OECD members from their entry year onward. "mean PRIV" gives the average financial development value, "mean GDP" the average income level, and "mean CO2" the average per capita carbon emissions.

OECD countries differ from non-OECD countries along several, potentially relevant dimensions. To this end, we focus on classic economic and environmental variables. In particular, for our sample of 36 OECD and 55 non-OECD countries, we observe from Table 6 that the mean GDP level is 38.3 resp. 8.7, mean financial development proxied via $PRIV$ is 94.5 resp. 57.2, and the mean per capita CO2 emissions are 2.0 resp. 0.8. To better understand the role of these country characteristics in determining effect heterogeneity, we divide countries into three

[21] Source: https://www.oecd.org/about/document/ratification-oecd-convention.htm, as of 05.05.2023.

[22] Since a country can be a non-member first and then become a member, it might appear in the non-OECD and in the OECD sample. For example, Slovenia joined the OECD on 21st of July in 2010, and hence, will be categorized as a non OECD member from 2004 to 2009 and as an OECD member from 2010 to 2020. For this reason, the total number of 91 countries exceeds the sample size of 86 unique countries in the baseline regression.

groups based on their initial level of either (i) financial development ($PRIV$), (ii) GDP per capita (GDP), or (iii) carbon emission per capita ($CO2$), and run our baseline regression for each of these samples separately. A country's initial level of a variable correspond to its first recorded value starting from 2004 and represent the initial state condition of that country. Categorization into a "high", "middle" or "low" initial state value is then based on the respective initial values' tertiles. The correlations between the three country characteristics are relatively high: 0.64 between $PRIV$ and GDP, 0.56 between $PRIV$ and $CO2$, and 0.57 between GDP and $CO2$. The mean initial values for each tertile, given in tables 7 and 15 in the bottom line, imply substantial differences in country characteristics between the three tertile groups.

Table 7: The table presents the regression results for the baseline equation (1.3) for $GINI$ for country subsamples based on different initial country characteristics. The initial levels of a variable correspond to its first recorded values starting from 2004 for every country and represent the initial state condition of the countries. We use either financial development, measured via private credit ($PRIV$), the gross domestic product (GDP), or the per capita carbon dioxide emission level ($CO2$) as country characteristic. The variable is then split into its tertiles and we use the tertile's threshold values to assign countries to the low, middle, or high initial level group.

	$GINI$								
country characteristic	PRIV			GDP			CO2		
tertile	high	middle	low	high	middle	low	high	middle	low
GI	0.8674*	0.7412	2.4913***	0.1791	2.4231**	3.192**	0.5486	1.2137	2.4709**
	(0.6749)	(1.9341)	(1.0428)	(1.3254)	(1.1812)	(1.5527)	(1.6062)	(1.0422)	(1.2725)
$GI \times GINI$ *lagged*	-0.0094	-0.0182	-0.0409**	0.0045	-0.04**	-0.056**	-0.0076	-0.0259*	-0.0424**
	(0.0115)	(0.0351)	(0.018)	(0.0261)	(0.0212)	(0.0265)	(0.0319)	(0.0197)	(0.0203)
control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2 adj	0.9927	0.9799	0.9955	0.9777	0.9896	0.9964	0.9874	0.9853	0.9972
n total	706	486	362	680	596	278	636	566	352
n unique	32	27	27	29	30	27	28	31	27
average effect ($\times$100)	0.3935	-0.2223	0.1567	0.3873	0.1586	-0.0221	0.1827	-0.1404	-0.1302
p-val	0.0204	0.2128	0.0399	0.1428	0.0713	0.3983	0.1814	0.137	0.0084
mean initial value	96.5534	38.3666	12.6803	24.4995	4.1884	0.6807	2.3821	1.5741	-0.4376

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *General notes*: see Appendix C. *Table-specific notes*: The "mean initial value" gives the average initial $PRIV$, GDP, or $CO2$ level in each of the thee groups (high, middle, low) of the corresponding variable.

Tables 7 and 15 report the regression results for the Gini coefficient and the top 5% income share, respectively. The results show that the effect of green investments on the Gini coefficient is positive and significant in countries with initially low levels of financial development, low to moderate levels of GDP per capita, and low per capita carbon dioxide emissions. This result is in-line with the finding on the OECD subsamples, namely, that "rich" countries seem less affected than "poor". We also find that in countries with high levels of financial development, an increase in green investments is linked to an increase in the top income shares. Intuitively, this result does not seem surprising: (i) green investment activity might benefit from a well-developed financial system, and (ii) green investment opportunities might be available to a restricted group of relatively rich people. Overall, our results in this section support the idea that the effect of green investments on inequality is heterogeneous across countries and is largely driven by developing countries, specifically those with lower levels of per capita income and carbon emissions.

5.4 Robustness

The association between green finance and inequality is robust to a number of robustness checks. These checks include altering the conditioning information set, excluding the interaction term from equation (1), and excluding countries that drive the green finance value. All regression results discussed in this section are delegated to Appendix E.

5.4.1 Altering the conditioning information set

When changing the control variable set, we have specific concerns in mind. First, we are worried that when controlling for environmental sustainability by means of including per capita carbon emissions, its focus is too narrow as it ignores large parts of other environmental concerns such as climate risk, water quality and biodiversity. Moreover, we have not yet accounted for environmental fiscal policies, but environmental taxes are one of the best tools to mitigate polluting behavior but they simultaneously risk increasing inequality (Chancel, 2022; Dennig, Budolfson, Fleurbaey, Siebert, & Socolow, 2015). We therefore want to account for these two types of environmental concerns. Second, institutional quality potentially influences inequality, and neglecting its impact might distort our results. Based on a similar concern, we include unemployment and interest in a third and fourth step.

(i) Country sustainability. One concern is that the definition of $CO2$ is too narrow as it ignores large parts of a country's overall sustainability due to its sole focus on carbon emissions.

For robustness, we thus consider two other environmental variables. First, we use the Country Sustainability Ranking (CSR) from RobecoSAM,[23] a proprietary dataset that rates 150 countries on their environmental, social, and governance performance twice a year. We use the mean environmental rating for each year, and denote the variable by CSR.[24] Second, we collect data on environmental tax revenue per capita (TXR) from the OECD Policy Instruments for the Environment (PINE) database.[25] We run the baseline regression replacing $CO2$ with CSR resp. TXR. Table 19 shows that the coefficients of GI remain significant and positive. When controlling for per capita tax revenues, the effects are larger than for the baseline output, and when controlling for country sustainability they are reduced. We conclude that including other environmental proxies than just $CO2$ does have an effect on the coefficient estimates' size, but the qualitative interpretation remains unchanged.

(ii) Institutional Quality. We extend our set of control variables to include institutional quality. Chong and Gradstein (2007) show that there is strong reversed causality in both directions between institutional quality and income inequality, with the feedback from inequality to institutional quality being especially pronounced. Moreover, H. Khan, Khan, and Zuojun (2022) establish a positive link between institutional quality and financial development in a panel data set covering 189 developing and emerging countries. We capture the notion of institutional quality with the following four variables, which are all common in the literature: (i) Rule of Law Index[26] (RLI); (ii) Property Rights Index[27] (PRI); (iii) Government Effectiveness[26] (GEI); and (iv) Control of Corruption Index[26] (CCI). We include each of the four institutional quality proxies in turn in the baseline equation for the Gini coefficient and the top 1% income share.

[23] https://www.robeco.com/ch/en/key-strengths/sustainable-investing/glossary/country-sustainability-ranking.html.

[24] The environmental dimension of CSR consists of a) environmental performance, an assessment of a country's environmental health, ecosystem vitality, and energy security, accessibility and sustainability, b) environmental risk, an assessment of the fatalities and economic losses due to climate change, weather-related losses, and natural disasters, and c) environmental status, an assessment of the diversity of the natural environment including resources.

[25] Source: https://www.oecd.org/environment/indicators-modelling-outlooks/policy-instrument-database/ as of 30.11.2022.

[26] Source: https://databank.worldbank.org/databases/governance-effectiveness, as of 18.01.2023.

[27] Secondary source: https://www.theglobaleconomy.com/rankings/herit_property_rights/, as of 16.05.2022. Original source is The Heritage Foundation.

Table 20 shows that the coefficients for green finance remain close to those of the baseline estimates. Hence, including institutional quality as an additional control variable does not alter our previous findings. Except for the Property Rights Index, the institutional quality controls enter the equation with negative coefficients. In other words, higher scores in the Rule of Law Index, the Government Effectiveness Index, or in the Control of Corruption Index are associated with less (top) income inequality. In contrast, a higher value in the Property Rights Index corresponds to a higher (top) income inequality.

(iii) Unemployment. In addition to the standard set of control variables, we include national unemployment rates from the World Bank[28]. Unemployment levels could potentially influence the income structure. "Green" sectors might see a need for more labor while "brown" sectors might have to cut jobs. This shift likely is not immediate and wages therefore adapt to the imbalance between labor supply and demand. We run the baseline equation for $GINI$ and TOP_5 with the additional control variable $UNMP$, and we assume that $UNMP$ is predetermined. The results are reported in Table 21. Interestingly, $UNMP$ enters the equation with negative coefficients, implying that higher levels of unemployment rates are associated with reductions in (top) inequality. The effects for GI, however, remain stable are very similar to those of the baseline equation.

(iv) Interest. In addition to the standard set of control variables, we include a measure of the annualized interest rate[29] ($INTR$). We share the concern of Schnabel (2021) that monetary policy may raise economic inequality by favoring the part of the population owning financial assets or wealth. We rerun the base equation for $GINI$ and TOP_5. Table 22 shows the results. Increasing interest rates, surprisingly, are negatively affected with inequality. The effect of green investment on the Gini coefficient reduces and looses significance, while the effect on top income inequality is magnified. The average marginal effect of green investments remains unchanged. We conclude that interest has a fair effect on the coefficient estimates of green investments and therefore is certainly strongly linked to inequality. However, the direction of the relationship

[28]Source: `https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS`, as of 07.02.2023.
[29]Source: `https://data.worldbank.org/indicator/FR.INR.RINR`, as of 27.04.2023.

between green finance and inequality is left unchanged as are the average effects.

5.4.2 Excluding the drivers of green investments

When analyzing the contribution of individual companies to green finance in the underlying green investment data (see figures 10a - 11b), two patterns emerge. While in the full sample of 87 countries companies most engaged in green finance activity tend to be from the United Kingdom, China, or the United States, the companies most engaged in green finance activity in the non-OECD sample are clearly Chinese ones. To ensure that the positive effect on inequality is not driven by the dominant role these countries play in green investing, we exclude all three from the sample and rerun the baseline regression. Table 23 gives the regression output. The effects of green investments are only slightly reduced and remain close to the original ones. The same applies to the average effect. We conclude that omitting major contributors of green investments, both from OECD and non-OECD countries, does not alter our findings.

5.4.3 Excluding the interaction term

There is concern about our argument that green investment levels depend on past inequality by means of the interaction term in equation (1). Indeed, we can not "prove" the validity of this assumption, but we can show the main regression results without the interaction term. Tables 24 and 25 show the corresponding results for the full sample resp. the OECD vs. non-OECD samples. Without the interaction term, the coefficient estimates correspond to the average effect, hence, we will compare the new results to the average effects from the baseline regressions in Tables 1 and 6. Overall, the Gini coefficient is not associated with green investments, while the effect on the top income share is significant and very close to the baseline average effect. Once the sample is split based on OECD membership, the same pattern as in the baseline result emerges. OECD countries do not show a significant association between green investments and inequality while the effect in non-OECD countries is pronounced and almost reaches the baseline average effect estimates. We conclude that omitting the interaction term in equation (1) does not alter our findings.

6 Mediation Analysis with Technological Change

A major source of growing inequality are technological advances (Schnabel, 2021), with top incomes benefiting disproportionately more from innovation than bottom income earners (Aghion et al., 2019). With ETI being capital spent on deploying low-carbon technology, we argue that technological change is a direct consequence of green investment flows, entailing initial costs on the income distribution. Indeed, green patents have seen a sharp increase over the past two decades (OECD, 2023), and show a significant correlation with green investments.[30]

With this in mind, we propose that green investments can have a positive impact on technological change in several ways. First, energy transition investments and proceeds of green bonds can provide funding for R&D activities focused on sustainable technologies, renewable energy, energy efficiency, and other environmentally friendly innovations. This financial support can help accelerate the development and deployment of new green technologies. Second, these technological advancements have an impact on the demand for different skill types in the labor market. The development and adoption of green technologies may require specialized skills and knowledge related to renewable energy, energy efficiency, waste management, sustainable agriculture, and other green sectors. This can create new job opportunities and increase the demand for individuals with the necessary skills, such as engineers, technicians, and researchers.

In this sense, this section shows that there exists a significant and positive relationship between green finance and innovation, and the effect of green investments on (top) income inequality is, at least partially, due to innovation and skill-biased technological change.

6.1 Data

Table 9 displays the summary statistics for the technological change data as well as for the newly introduced control variables.

Indicator of technological change and innovation. The indicator to measure technological change and innovation consists of patents in environmental related technologies from the

[30] The correlation of the green patent data ($PATe$) (see section 6.1) with GI for the countries in the sample is 0.3831.

OECD Patent Database.[31] Patent data are an important measure of innovation since they reflect the inventive power of countries or firms. They are also a resource for the study of technological change. Patents cover a wide range of products and technologies, which otherwise lack data records. Note that some countries display different patenting behavior and regulations, making comparison over time and between countries difficult. Even though our analysis considers different time periods, we will compare within country changes, which alleviates the above mentioned problem to some degree. The indicator consists of the sum of patents in environmental related technologies granted by the European Patent Office and by the US Patent and Trademark Office. We take the natural logarithm of the sum and denote the indicator by $PATe$. To appropriately capture the overall technological innovation in a country, patents are assigned to countries based on the inventor's country of residence. The assignment to a given year is based on the priority date, that is the date that corresponds to the first filing worldwide, and it is therefore closest to the invention date. All variables are based on fractional counts: A patent invented by several inventors is allocated to their residence country relative to each inventor's contribution., thereby preventing multiple counting. For example, a patent co-invented by 1 French, 1 US American and 2 German residents will be counted as 1/4th of a patent for France, 1/4th of a patent for the USA, and 1/2 of a patent for Germany. Previous research by Flammer (2018) used green patent data as a measure for green innovation, and found that green bonds are positively associated with green innovation.

Control variables and exogeneity assumptions. The control variable set X additionally includes foreign direct investments[32] (FDI) and the unemployment rate[33] ($UNMP$) in both equations (3) and (4) of the moderated mediation analysis. Both variables are frequently used in conjunction with innovation (see e.g. Aghion et al., 2019; Huang, Chen, Lei, & Zhang, 2022; M. L. Wang, 2023). FDI and $UNMP$ are assumed exogenous.

[31] Source: https://stats.oecd.org/, OECD Directorate for Science, Technology and Industry, Economic Analysis & Statistics Division's patents in environmental related technologies dataset, last updated October 2022.
[32] Source: https://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS, as of 07.02.2023.
[33] Source: https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS, as of 07.02.2023.

6.2 Estimation strategy via moderated mediation

Mediation analysis is a statistical technique used to understand the mechanism through which an independent variable influences a dependent variable by introducing one or more intermediate variables, known as mediators (Agler & De Boeck, 2017). In their most basic form, mediation analyses aim to test three hypotheses: (i) the independent variable has a significant effect on the mediator variable; (ii) the mediator variable has a significant effect on the dependent variable; (iii) the effect of the independent variable on the dependent variable reduces or becomes non-significant when controlling for the mediator variable.

We employ a moderated mediation approach (Muller, Judd, & Yzerbyt, 2005) to explore the indirect effect of green investments on income inequality, i.e. to assess the extent to which the relationship between the two variables is mediated by green patents. Moderated mediation extends traditional mediation analysis by examining whether the indirect effect of green finance on inequality through a mediator variable is contingent upon the level of a moderating variable. Because green investment is interacted with lagged inequality, lagged inequality moderates the effect of green investing. This allows for a more nuanced understanding of the underlying mechanism and how this mechanism may operate differently depending on the lagged inequality levels. Denoting the mediator by M, figure 12 illustrates this relationship graphically, and the regression equations (3) and (4) represent these relationships mathematically.

$$M_{i,t} = \beta_1 GI_{i,t} + X'_{i,t}\beta_2 + \delta_t + c_i + \epsilon_{i,t}. \tag{3}$$

$$\begin{aligned} INEQ_{i,t} =& \beta_3 GI_{i,t} + \beta_4 M_{i,t} + \beta_5 INEQ_{i,t-1} + \beta_6 (GI_{i,t} \times INEQ_{i,t-1}) \\ &+ \beta_7 (M_{i,t} \times INEQ_{i,t-1}) + X'_{i,t}\beta_8 + \delta_t + c_i + \epsilon_{i,t}. \end{aligned} \tag{4}$$

In line with regression (1), δ_t are the time-specific effects, c_i the country-specific effects, and X is the complete set of control variables.[34] For a successful transmission of the effect through innovation, green investments must significantly impact patents (the mediator M) in (3). We therefore expect the coefficient β_1 to be significant. In the case of complete mediation, the effect of GI on inequality (β_3) is no longer significant in (4). In this case, the effect is fully channeled through green patents. The underlying rationale is that if the mediator explains the effect of

[34] SEC, GOV, $INFL$, TRD, $MCAP$, $PRIV$, GDP, $CO2$, FDI, $UNMP$.

the explanatory on the dependent variable, then the effect of the explanatory variable can be expected to diminish in absolute terms and become insignificant in the presence of the mediator. In case of partial mediation, only part of the effect is channeled through the mediator, and the direct effect of green finance on inequality persists, but to a lesser degree. This corresponds to β_3 decreasing in absolute terms and staying significant.

The moderation analysis allows us to uncover the direct effect, the indirect effect via green patents, and the total effect on inequality for a $p\%$ change in green finance. The direct effect corresponds to the marginal effect of green investments on inequality, whereas the indirect effect corresponds to the marginal effect of green investments on inequality via green patents.[35] Each country has its own effect size since effects depend on lagged inequality levels. For simplicity, we report the average effect size for a 1% change only.

We continue to use the SGMM estimator to uncover the various effects. We assume that the control GDP and green investments GI are predetermined in equation (3), meaning that past shocks to patenting behavior potentially have an influence on today's per capita GDP level and the exertion of green finance efforts. Using patent data as an outcome, we do not assume any variable to be endogenous.

6.3 Results

Table 8 reports the regression results for the moderated mediation analysis. The results for equation (3) show that an increase in green investments is positively and significantly associated with an increase in the number of green patents. The results for equation (4) suggest that while the positive effect of green investment amounts on (top) income inequality is obliterated, green patents show a significant effect. In the presence of green patents, the effect of green investments no longer persists and instead is replaced by the effect of green patents. In other words, full mediation takes place and the positive effect of green investments on inequality is channeled

[35] Differentiating equation (4) with respect to GI yields the direct effect $ln((100+p)/100) \times (\beta_3 + \beta_6 INEQ_{i,t-1})$. The indirect effect is computed as the marginal effect of green investments on green patents in (3) times the marginal effect of green patents on inequality in (4), yielding $ln((100+p)/100)^2 \times \beta_1 \times (\beta_4 + \beta_7 INEQ_{i,t-1})$ for logarithmic defined mediator variables and $ln((100+p)/100) \times \beta_1 \times (\beta_4 + \beta_7 INEQ_{i,t-1})$ otherwise. The total effect is then computed as the sum of the direct and the indirect effect.

via green patents. This result is supported by the observation that the average total effect (see bottom panel of table 8) is relatively close to the average effect in the baseline regression.

Table 8: This table reports the main moderated mediation regression results for innovation measured via green patents ($PATe$). Green patents channel the effect of green investment on (top) income inequality. For a full output overview we refer the reader to table 26.

equation	(3)	(4)	
outcome	$PATe$	$GINI$	TOP_5
mediator		$PATe$	$PATe$
GI	0.1058***	0.396	0.0171
	(0.0286)	(0.3698)	(0.2934)
$PATe$		1.5044***	0.9282***
		(0.299)	(0.2511)
R^2 adj	0.661	0.994	0.975
n total	1142	1142	1142
n unique	64	64	64
average direct effect		0.1493	0.1912
average indirect effect		0.0001	0.0001
average total effect		0.1494	0.1913

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *General notes*: see Appendix C. *Table-specific notes:* The average effects are scaled by 100.

6.4 Robustness

To show the validity of the channel mechanism, we replace the green patent measure $PATe$ by three different measures of technological change and innovation. First, we take the natural logarithm of the number of total patent applications[36], denoted as PAT. Second, we include research and development expenditure as a share of GDP[37], denoted as RD. The data measures public and private expenditure on research, which is a key indicator of the effort to obtain a competitive advantage in science and technology. Finally, to capture the labor market effects induced by the rising demand to innovate, we use the number of people employed in professional, scientific, and technical activities as a share of the total number of people employed[38], denoted as EMP. When the mediator is total patents, we assume that GDP per capita and green investments are predetermined in equation (3). When the mediator corresponds to research and

[36]Source: https://data.worldbank.org/indicator/IP.PAT.RESD, as of 19.11.2022.
[37]Source: https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS, as of 01.06.2023.
[38]Source: OECD.Stat. 3. Population and employment by main activity. We use the domestic measurement concept. From the available data we use the latest International Standard Industry Classification Revision 4 sectors. https://stats.oecd.org/Index.aspx?DataSetCode=SNA_TABLE3, as of 06.06.2023.

development expenditures, we assume green investments to be predetermined and government expenditures to be endogenous in equation (3). Finally, if the mediator is the share of employed in research related fields, we assume GDP per capita and green investments to be predetermined while we assume per capita carbon emissions to be endogenous in equation (3).

The results in Table 27 confirm the conclusion that technological change and innovation explains the positive effect of green investments on inequality. The mediation is pronounced for all three robustness indicators; the effects of green investments are flipped and consistently have negative signs while all three mediators show strong significant positive links with inequality.

7 Discussion on the role of carbon emissions

It is widely acknowledged that climate change can have a significant impact on economic inequality, both within and across countries (Burke, Hsiang, & Miguel, 2015; Diffenbaugh & Burke, 2019; Hallegatte & Rozenberg, 2017). Within countries, climate change can impact economic inequality in several ways. It can lead to economic losses in sectors such as agriculture, fishing, and forestry, affecting the livelihoods of those dependent on these industries Guivarch et al. (2021). It can therefore result in job losses or reduced income for individuals, particularly in sectors vulnerable to climate impacts. This in turn can hinder educational attainment and exacerbate unemployment, further widening economic inequality. Climate change can also result in increased frequency and intensity of extreme weather events, with low-income communities often residing in areas with inadequate infrastructure and thus more likely to experience damage to their property Islam and Winkel (2017).

With this in mind, a second potential pathway from green finance efforts to inequality via climate change effects imposes itself. While the key purpose of green investments is climate change mitigation, adaptation, and environmental protection, we argue that it is possible for such large scale investments to inadvertently contribute to carbon emissions and therefore to climate change, at least in the short term. While the long-term goal of energy transitions investments is the reduction of emissions, a short-term rise in investment emissions and within-country carbon inequality were unsurprising (Chancel, 2022), mainly due to the environmental impact of capital formation (Södersten, Wood, & Hertwich, 2017). Investment emissions are emissions attributed to capital formation and firm ownership. They are based on decisions made by capital owners about investments in the production process, such as the construction of machines or factories. On the other hand, consumption emissions stem from the direct use of energy or its indirect use (for example energy embedded in the production of goods and services) (Chancel, 2022). Indeed, capital investments can push environmental degradation driven by the impacts of infrastructure development (Kobayakawa, 2022; Södersten et al., 2017).

Another avenue of thoughts relates to carbon inequality, which captures the fact that carbon emissions are not equally distributed across the population. Chancel and Piketty (2015) show that within country carbon inequality is associated with income inequality and has on average increased. Wealthier individuals tend to have higher carbon emissions due to higher consumption patterns and higher investment participation. The richest 10% of the worldwide population generated almost 48% of total GHG emission in 2019. In comparison, the poorest 50% of the global population accounted for only 12% of total global GHG emissions Chancel, Bothe, and Voituriez (2023). Importantly, carbon inequality is mainly driven by investment emissions, with the bulk of total emissions from the global top 1% of the world population stemming from their investments rather than from their consumption (Chancel, 2022). While the majority of individuals derive their income from labor, the richest generate most of their income from the returns on their investments (Dabi et al., 2022), with up to 70% of their emissions attributed to their investments (Chancel, 2022).

For a simple diagnostic insight into this chain of relationships, we run two simple regressions: capital formation on green finance, and investment emissions on capital formation. These regressions capture the following chain of events: green investments → capital formation → investment emissions. Further details on the data and estimation approach are provided in Appendix F. We take the results from table 28 as first reassuring evidence that an increase in green investment efforts is indeed linked to more investment emissions via capital formation.

8 Concluding Discussion

Finance has arguably been undergoing a substantial paradigm shift, with concerns beyond profit and risk playing an increasingly important role. This paper argues for the need to turn attention to quantifying the prospective short- and long-term effects of green finance on social welfare. Towards this end, we looked at the relationship between green investments and income inequality and established two main results. First, we found that higher green investment amounts are positively associated with measures of overall and top income inequality. This relationship is strongest for countries with low to moderate levels of GDP per capita, financial development, and per capita carbon dioxide emissions. Second, the moderated mediation results indicate that the positive association between green investment amounts and (top) income inequality is indeed transmitted through innovation and skill-biased technological change. In our study we addressed frequent concerns of greenwashing, general investment effects, and the role of emissions and climate change as an alternative channel. The results presented are robust to various empirical changes. The following concerns could be raised by our study.

First, our choice of data is limited by practical considerations. There is no standard measurement of green finance activities within and across countries, and existing proxies are plagued by historical limitations. With this in mind, we use a novel dataset from Bloomberg New Energy Finance on energy transition investments, renewable energy transactions and sustainable debt that provides a broad coverage in terms of countries and years. Future work should revisit our analyses with longer histories and potentially novel standardized measurements of green finance.

Second, the strong associations between green investment and inequality may reflect a mixing of effects with other variables. Determining the drivers of income inequality is a complex issue with great variation across countries. Some common variables associated with increased inequality include weakening protection for labor, skill-biased technological change, lack of financial inclusion in developing countries, and growing capital markets in developed countries. Yet, the coefficient of green investments remains positive and significant when we include an array of such variables that might directly or indirectly affect inequality.

Third, our study does not claim to provide evidence for a causal channel from green finance to inequality. To be able to argue that the positive association between green investments and (top) income inequality at least partly reflects a causal relationship, one could, for example, carry out an instrumental variables analysis. However, instrumenting for green finance in a consistent and intuitive way across different countries is highly complex, if at all feasible. That said, we do make a case against reverse causality: our methodological choice of the system generalized method of moments estimator addresses such concerns. A causal study moreover requires to determine the correct lag of green investments since the effect on inequality might require several periods to fully develop, also in case of mediation via technological change. Based on the currently available evidence from the literature, we have to leave this task for future investigation.

Fourth, our study does not account for potentially important spillover effects across countries. Finally, note that our results focus on the relatively short-term effects of green investments. The lagged associations between green investments and inequality indicate that the relationship weakens after 4 years. This is in line with the literature on innovation and top income inequality (Aghion et al., 2019). While we also argue for short-term investment emissions channeling the relationship to inequality, the long-term environmental effects due to green finance are yet to materialize. Whether a future reduction of emissions might bring about a reduction in inequality is left for future work.

Notwithstanding, our insights are a first step towards assessing the overall potential impact of green investments on issues that go beyond environmental concerns. Our findings shed light on the trade-off between environmentally oriented finance and the distribution of financial burdens of environmental changes across the population. Our results motivate additional work to further understand how large scale flows into green investments might affect social welfare more broadly.

On the other hand, recall that our analysis also indicates that lower income shares are positively associated with green investments, but to a lower degree. While income inequality is a complex and highly debated topic, there are arguments that suggest increases in top income inequality may not necessarily be entirely bad, especially if there are benefits to the rest of the income distribution. There are potential nuances in the relationship between green finance and inequality, which policymakers can consider when designing economic and social policies related to green finance. As Klenert and Fleurbaey (2021) note, climate and distributional policy can generally not be separated. Along similar lines, our results simply point to the fact that the green finance transition comes with social welfare implications, and thus promote the implementation of a comprehensive policy approach that addresses both economic inequality and environmental sustainability.

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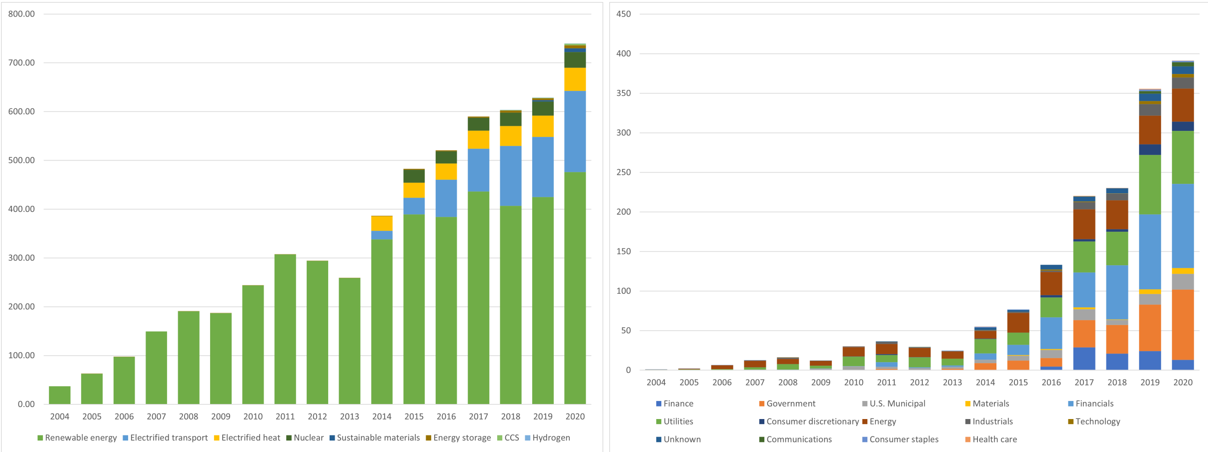
A Data and Descriptive Statistics



(a) Energy transition investments by sectors (b) Green debt by issuer industry

Figure 1: The figure shows the components of our green finance variable in more detail: energy transition investments (ETI) by sectors (Panel 1a) and green debt (GD) amount issued by issuer industry (Panel 1b), both in billion USD for the years 2004 to 2020. The data source is Bloomberg New Energy Finance.

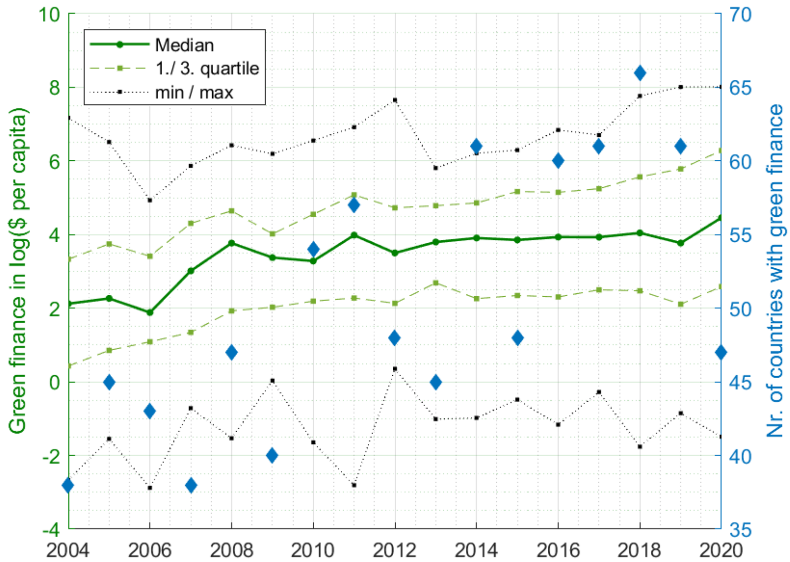


Figure 2: The figure shows the final green investment (GI) variable's descriptive plot based on the years 2004 to 2020, and the sample used in the following regression analysis (a total of 87 different countries are involved). The solid green line indicates the median green finance level while the dashed light green lines represent the first resp. third quartile endpoints. The dot-dashed black line shows the minimum resp. maximum value of GI. The blue diamond shapes indicate the number of countries present in the sample in each year. [REMARK: update plot axis labels]

Countries covered The analysis includes the following 87 countries:

United Arab Emirates, Australia, Austria, Belgium, Burkina Faso, Bangladesh, Bulgaria, Bolivia, Brazil, Canada, Switzerland, Chile, China, Cote dIvoire, Colombia, Costa Rica, Cyprus, Czechia, Germany, Denmark, Dominican Republic, Egypt, Spain, Estonia, Finland, France, United Kingdom, Georgia, Ghana, Greece, Hong Kong SAR, China, Croatia, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Jordan, Japan, Kazakhstan, Kenya, Cambodia, South Korea, Sri Lanka, Lithuania, Luxembourg, Latvia, Morocco, Mexico, North Macedonia, Mali, Mongolia, Mauritius, Malaysia, Niger, Nigeria, Netherlands, Norway, New Zealand, Oman, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Romania, Russia, Rwanda, Saudi Arabia,

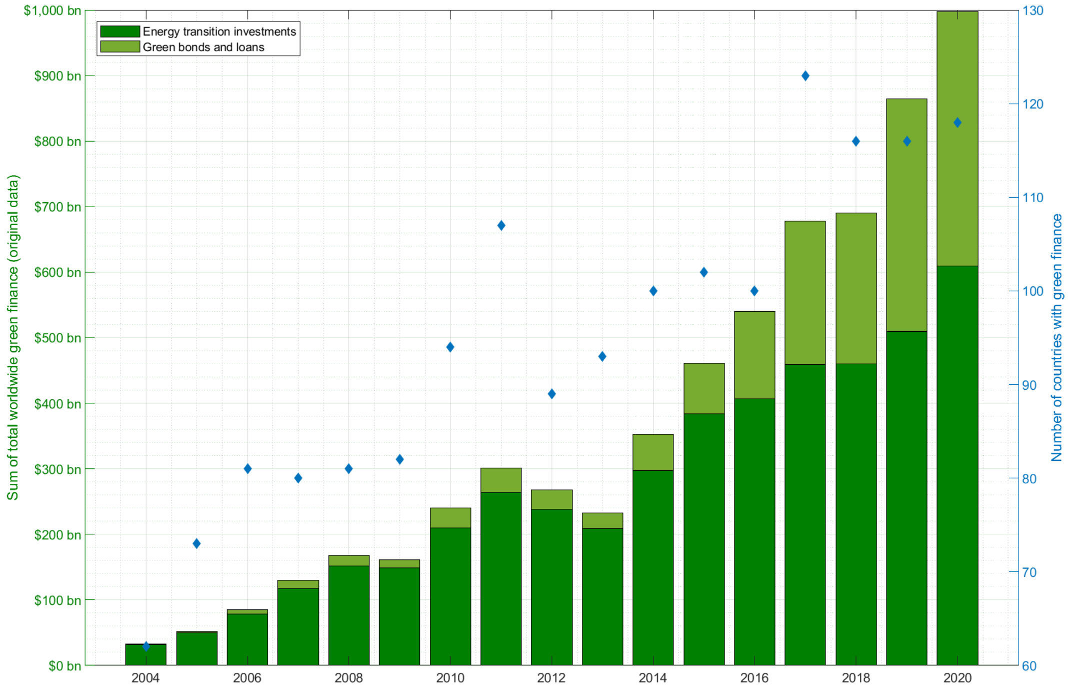


Figure 3: The figure shows the year-wise aggregated energy transition investments (dark green) and green debt amounts issued (light green) for the years 2004 to 2020 in USD. The right vertical axis shows the number of countries that engage in green finance in each year. The data source is Bloomberg New Energy Finance.

Senegal, Singapore, Serbia, Slovakia, Slovenia, Sweden, Thailand, Tunisia, Turkey, Tanzania, Uganda, Ukraine, Uruguay, United States of America, Venezuela

Descriptive Statistics We want to provide insight into the relationship of green investments with various economic dimensions. First, we consider the relationship with the control variables GDP per capita (GDP) and financial and stock market development ($PRIV$, $MCAP$). The correlation of GI with GDP is 0.64 while it is 0.55 with $PRIV$ and 0.25 with $MCAP$. We conclude that per capita green investing is higher in countries with high per capita GDP and financial development. green investments are strongly positively correlated with per capita carbon emissions ($CO2$) with a coefficient of 0.44. This indicates that per capita green investments are more pronounced in countries with higher per capita carbon emissions. Figure 5 shows the scatter plots between GI and all four considered variables including the least squares regression line.

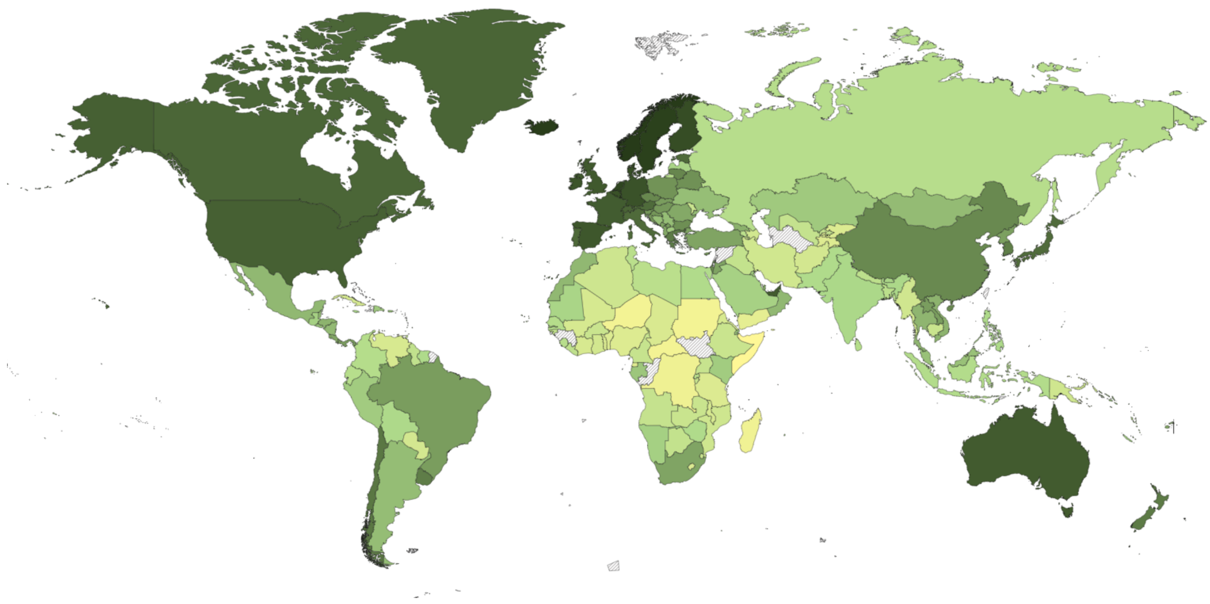


Figure 4: The figure shows the total green finance efforts in natural logarithm for all countries in the sample. "Total" corresponds to the entire investment sum for each country (the data underlying GI prior to the logarithmic transformation) summed from 2004 to 2020. Higher effort levels correspond to darker green while lighter yellow corresponds to lower efforts. Countries not covered in our sample are displayed in gray stripes. Over the whole time period 2004-2020, Western Europe and North America are leaders, closely followed by China, Australia, New Zealand, the United Arab Emirates, Chile and Uruguay.

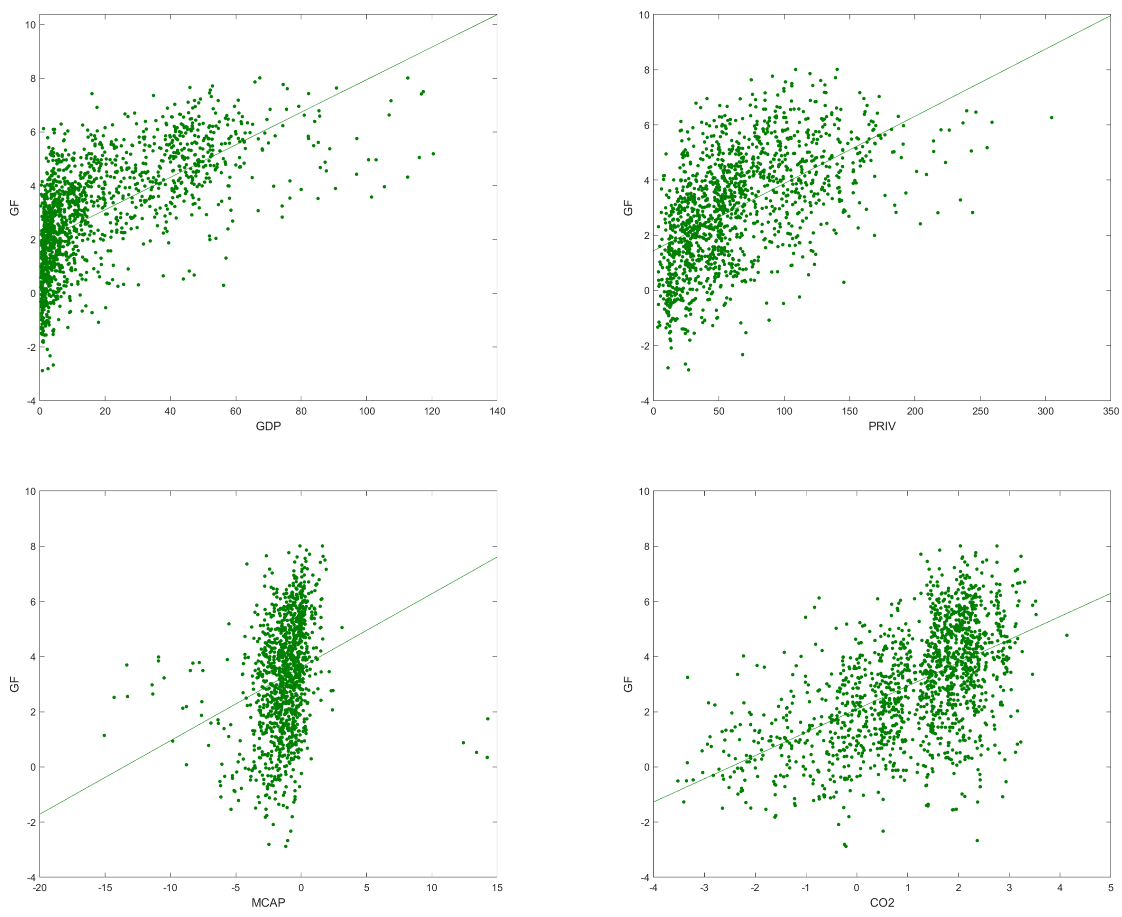


Figure 5: Correlation plots of green investments (GI) and various control variables including the least squares line. Computations are based on th e87 countries appearing in the analysis for the years 2004 to 2020. From left to right and top to bottom: Scatterplot of GI against GDP per capita, financial development, stock market development, and per capita carbon emissions.

Table 9: The table shows the summary statistics for each variable based on the full sample of 87 countries over the years 2004 to 2020 for our measure of green finance and its components, for other investment data, for the various inequality measures (relative and absolute), for the control variables, and lastly for innovation and technological change proxies. We provide the following information (column-wise): the number of observations n, mean, standard deviation (SD), quartiles' thresholds, minimum and maximum.

		n	mean	SD	min	p25	p50	p75	max
Green investment	GI	1162	3.29	2.03	-2.88	1.93	3.43	4.81	8.01
	ETI	1131	3.05	1.92	-2.88	1.69	3.26	4.52	7.44
	GD	540	2.92	2.13	-5.92	1.53	3.05	4.51	7.99
Other investment	TI	925	8.71	0.69	5.99	8.27	8.81	9.19	10.79
	RET	963	2.53	2.04	-7.80	1.15	2.84	3.99	7.54
	$RETi$	883	2.17	1.90	-5.73	0.86	2.42	3.57	6.79
Inequality	$GINI$	1479	54.43	8.88	37.41	46.96	54.60	60.70	76.17
	G_{90}	1479	0.20	0.04	0.11	0.17	0.20	0.22	0.35
	G_{95}	1479	0.34	0.06	0.21	0.29	0.34	0.37	0.51
	G_{99}	1479	0.47	0.08	0.30	0.40	0.47	0.52	0.69
	TOP_{10}	1479	43.21	9.07	26.43	34.62	43.22	49.69	67.83
	TOP_{5}	1479	31.85	8.07	16.95	24.46	31.67	37.88	54.56
	TOP_{1}	1479	15.17	4.82	5.62	11.33	14.87	18.44	35.87
	TOP_{01}	1479	5.02	2.13	1.09	3.64	4.76	6.00	22.16
	TOP_{10a}	1479	11.53	0.80	9.38	10.99	11.67	12.09	13.67
	TOP_{1a}	1479	12.76	0.82	10.41	12.24	12.90	13.31	15.14
	TOP_{01a}	1479	13.92	0.92	11.22	13.35	14.04	14.58	16.71
Controls	SEC	1253	91.57	27.18	8.71	82.47	97.52	105.37	163.93
	GOV	1456	16.10	4.90	3.46	12.33	16.51	19.49	30.00
	$INFL$	1466	4.28	8.68	-4.48	1.28	2.77	5.42	254.95
	TRD	1471	91.06	63.84	20.72	53.37	73.28	110.99	442.62
	$MCAP$	1356	-1.35	2.06	-14.32	-2.18	-1.15	-0.32	14.28
	GDP	1473	20.36	22.49	0.27	3.23	10.87	34.55	123.68
	$PRIV$	1436	67.30	46.79	0.19	30.98	54.60	94.77	304.58
	$CO2$	1479	1.21	1.37	-3.04	0.57	1.61	2.16	3.33
	FDI	1470	5.94	16.96	-57.53	1.46	2.90	5.32	279.35
	$UNMP$	1479	7.04	4.81	0.14	3.94	5.86	8.64	37.25
Innovation, technological change	$PATe$	921	3.33	2.54	-2.95	1.39	3.07	5.37	9.70
	PAT	1229	6.35	2.54	0.00	4.68	6.35	7.68	14.15
	RD	667	1.27	1.01	0.04	0.45	0.95	1.84	4.41
	EMP	712	9.71	3.66	1.00	7.16	9.64	11.51	21.96

B Econometric Methodology

$$y_{i,t} = \alpha y_{i,t-1} + x'_{i,t}\beta + c_i + \delta_t + \epsilon_{i,t} \tag{A}$$
$$\Delta y_{i,t} = \alpha \Delta y_{i,t-1} + \Delta x'_{i,t}\beta + \Delta\delta_t + \Delta\epsilon_{i,t} \tag{B}$$

SGMM consists of a system of two equations, one in levels (A) and one in differences (B), where (B) is obtained from (A) by subtracting y_{t-1} on both sides. This procedure removes the time invariant variables but keeps the coefficients α and β untransformed. y is the dynamic dependent variable, x are the k, $k = 1, \dots, K$, explanatory variables, c_i is the individual specific effect, δ_t are the time-specific effects, ϵ is the error term, and Δ at time t is the shorthand notation for the difference from t to $t-1$ for the variable following Δ. With fixed effects, the individual specific effect c_i is a random variable that may be correlated with the explanatory variables. It can be thought of as an individual-specific intercept. We follow (p.115 Roodman, 2009) who observes that introducing any dummy that is 0 or 1 for almost all individuals might cause a bias in the same way as the dynamic panel bias in within-group estimators for fixed effect panels (see Nickell, 1981). For this reason we explicitly do not use individual dummies in equation (A) during estimation.

The difference GMM estimator of Arellano and Bond (1991) is applied to the regression equation (B). Instrumental variables are needed to overcome the potential reversed causality introduced by an endogenous y or a predetermined x. By definition, the error term $\Delta\epsilon_t = \epsilon_t - \epsilon_{t-1}$ is correlated with $\Delta y_{t-1} = y_{t-1} - y_{t-2}$ because $E[y_{t-1}\epsilon_{t-1}] \neq 0$. For a predetermined x, note that $E[\Delta x_t \Delta\epsilon_t] \neq 0$ because $E[x_t\epsilon_{t-1}] \neq 0$. By a suitable choice of instruments these problems can be overcome. For any predetermined variable x_t its difference $\Delta x_t = x_t - x_{t-1}$ is instrumented with the level x_{t-1}. The resulting moment conditions are $E[x_{t-s}\Delta\epsilon_t] = 0$, $s \geq 1$, t. For any endogenous variable y, its difference Δy_{t-1} is instrumented with its lagged level y_{t-2}, yielding the moment conditions $E[y_{t-s}\Delta\epsilon_t] = 0$, $s \geq 2$, $\forall t$. A drawback of difference GMM is that after differencing, the disturbances $\Delta\epsilon_t$ may be far from independent and reducing accuracy. To see this note that $\Delta\epsilon_t$ can be correlated with $\Delta\epsilon_{t-1}$ because they share the common component ϵ_{t-1} (Roodman, 2009). Moreover, the difference GMM estimator suffers from a potential weak instrument problem. It arises because lagged level values of x often perform poorly when predicting its future differences. This leads to potential bias in finite samples and poor precision, even asymptotically (Alonso-Borrego & Arellano, 1999).

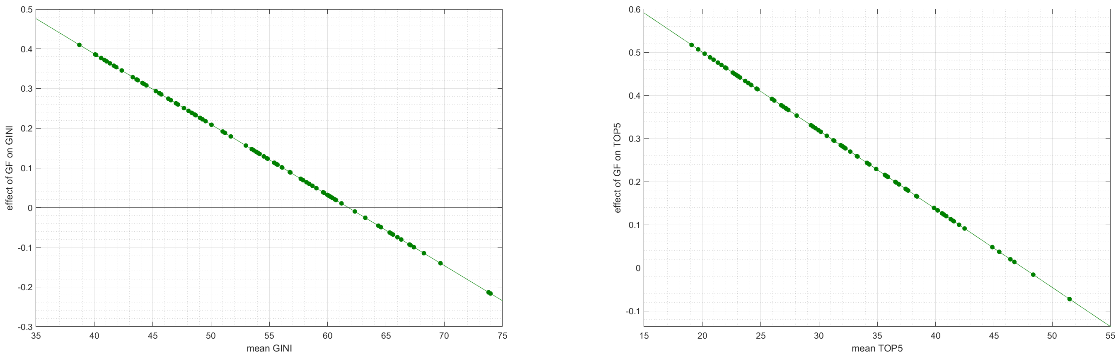
The SGMM estimator improves on the difference GMM estimator by taking into account the information contained in the level specification (A). The increase of available instruments in SGMM can dramatically increase efficiency (Roodman, 2009). The main problem in equation (A) arises from the fact that the explanatory variables are correlated with the error term, that now contains the unobserved individual specific effects. This can be summarized as $E[x_t(c+\epsilon_t)] \neq 0$, $\forall t$. To solve this problem, the underlying assumption is that $E\left[x_t(c+\epsilon_t)\right] = E\left[x_s(c+\epsilon_t)\right]$, $\forall s,t$. This allows the construction of an instrumental variable that exploits that differences in x or y set the moment condition to zero. Finally, predetermined x_t are instrumented with their differences Δx_t. The resulting moment conditions are $E[\Delta x_t(c+\epsilon_t)] = 0$, $\forall t$. Endogenous y_{t-1} are instrumented with their first differences Δy_{t-1}, yielding the moment conditions $E[\Delta y_{t-1}(c+\epsilon_t)] = 0$, $\forall t$. Following Holtz-Eakin et al. (1988) we substitute zeros for missing instruments.

To make SGMM work, standard GMM is used with the only difference, that a system of equations is used, and matrices must be built accordingly. For example, the vector containing the dependent variable must consist of y and Δy, the same holds true for the matrix of regressors.

C Table Notes

Robust standard errors in parentheses. We allow for within-country correlation (autocorrelation) but no between country correlation. The regression includes time-invariant effects. The regression does not include country specific effects since Roodman (2009, p.115) explicitly advises against including such binary variables. “J statistic” is the Hansen J test: the null hypothesis is that all overidentifying restrictions (e.g. the instrumental variables) are valid. The p-value for the J statistic is named as “J p-val”, and a value close to one is reassuring but it is still open to debate whether the choice of instruments is a good one. “n mom” is the number of moment conditions. “n total” provides the number of country-year combinations available e.g. the number of data points used while “n unique” gives the number of unique countries used in the regression. “average INEQ lagged” gives the average value of $INEQ_{i,t-1}$ over the full sample. This value is needed to compute the “average effect” with the formula $\ln(1.01) \times (\beta_1 + \beta_3 \overline{INEQ})$ based on equation (1). This is the marginal effect of green finance (partial derivative) for a 1% change in green finance evaluated at the average lagged inequality level. The values reported are scaled up by a factor of 100 to avoid zero entries due to rounding. The standard error “SE” of the average effect is derived from the variance-covariance matrix of the parameter estimates. The formula is $\sqrt{\ln(1.01)^2 \times \left[\mathrm{VAR}(\beta_1) + \mathrm{VAR}(\beta_3)\overline{INEQ}^2 + 2\mathrm{COV}(\beta_1, \beta_3)\overline{INEQ}\right]}$. The corresponding p-value “p-val” is based on the t-distribution with degrees of freedom equal to “n total” minus the number of estimated coefficients in the model.

D Results Part I



(a) Marginal effects for $GINI$.

(b) Marginal effects for TOP_5.

Figure 6: The two figures show the marginal effect on the Gini coefficient resp. the top 5% income share for a 1% change of green investments. The marginal effect is computed by differentiating equation (1) with respect to green finance and using the average lagged inequality level for every country i over the period 2004 to 2020, thus representing a country by a single data point. Coefficients are taken from the baseline regression (1.3) results. Only countries appearing in the regression (1.3) are included in the figure. [REMARK: update. give correct interpretation!]

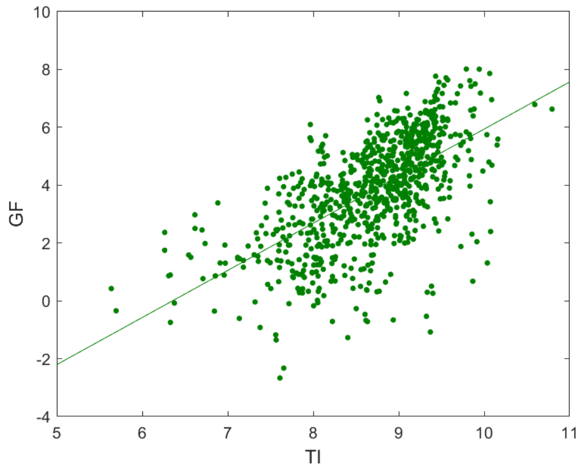


Figure 7: Scatterplot of total investments (TI) against green investments (GI) including the least squares regression line.

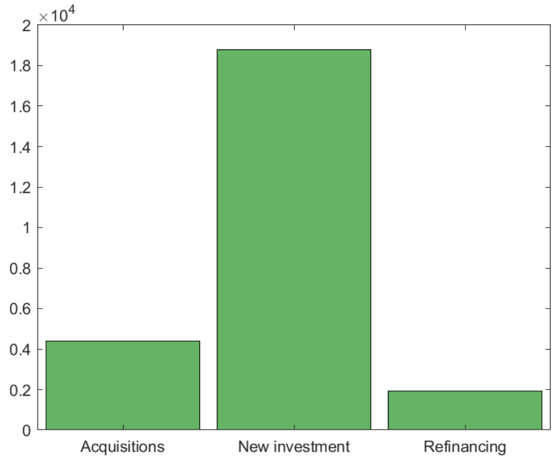
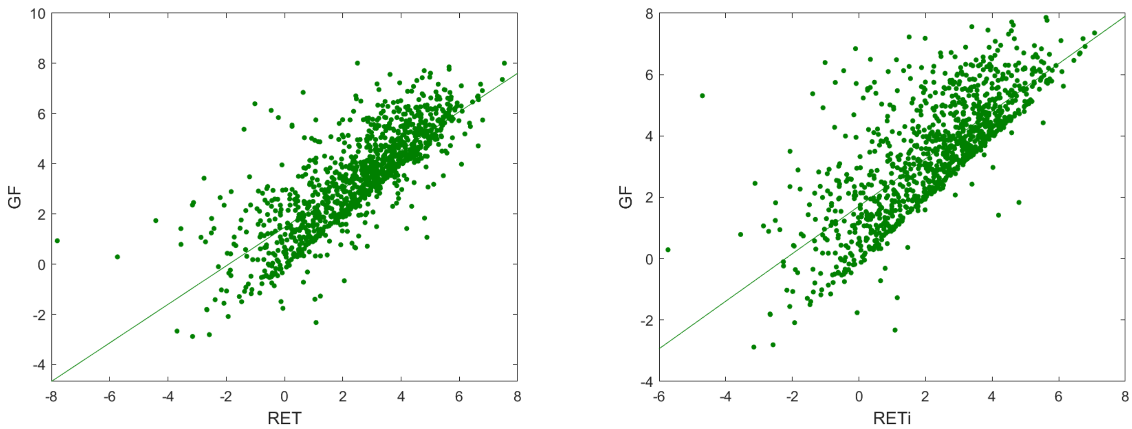


Figure 8: This histogram shows the number of renewable energy transaction (RET) deals within each of the investment type categories (acquisitions, new investments, or refinancing). Computations are based on the sample covering the years 2004 to 2020.



(a)

(b)

Figure 9: The figure shows the relationship between renewable energy transactions (RET) and green finance (GI) in panel 9a and RET's new investments only subset ($RETi$) against green finance (GI) in panel 9b. [Remark: plot axis GI instead of GF]

Table 10: The table presents the base regression 1 results for overall inequality ($GINI$) and the top 5% income share (TOP_5) for the subsequent addition of control variables.

	GINI				TOP_5			
specification	(1.1)	(1.2)	(1.3)	(1.4)	(1.1)	(1.2)	(1.3)	(1.4)
CO2			-0.9958***	-1.3332***			-1.075***	-1.4423***
			(0.1202)	(0.1788)			(0.1387)	(0.1949)
GDP		-0.0735***	-0.066***	-0.0548***		-0.0751***	-0.0648***	-0.0509***
		(0.0046)	(0.0033)	(0.0036)		(0.0051)	(0.0045)	(0.0049)
GF	0.4151**	1.2704***	1.0983***	2.066***	0.8876***	1.0168***	0.8642***	1.4898***
	(0.1925)	(0.1787)	(0.1686)	(0.2729)	(0.1807)	(0.1441)	(0.1291)	(0.2299)
GF2				-0.0723***				-0.0641***
				(0.0119)				(0.0117)
GF_GINIl	-0.0065**	-0.0214***	-0.0178***	-0.0268***				
	(0.0036)	(0.0033)	(0.0031)	(0.0041)				
GF_TOP5l					-0.0217***	-0.0235***	-0.0182***	-0.0241***
					(0.0055)	(0.0046)	(0.0042)	(0.0058)
GINIl	0.7883***	0.7975***	0.7835***	0.7992***				
	(0.0215)	(0.0183)	(0.0148)	(0.0194)				
GOV	-0.0187	-0.0674***	-0.0134	-0.0006	-0.1157***	-0.1728***	-0.1283***	-0.1196***
	(0.0314)	(0.0169)	(0.0191)	(0.0336)	(0.0302)	(0.0244)	(0.0256)	(0.0317)
INFL	0.1097***	0.1101***	0.1093***	0.1028***	0.0446***	0.087***	0.0859***	0.0821***
	(0.02)	(0.0141)	(0.0145)	(0.0188)	(0.0184)	(0.021)	(0.0241)	(0.0255)
MCAP	0.2006***	-0.0468**	0.0363**	0.1051*	0.4665***	0.1616***	0.2466***	0.3048***
	(0.0568)	(0.0233)	(0.0188)	(0.0657)	(0.057)	(0.0424)	(0.0426)	(0.054)
PRIV		-0.0117***	-0.014***	-0.017***		-0.018***	-0.0186***	-0.0199***
		(0.0011)	(0.0012)	(0.0016)		(0.0013)	(0.0017)	(0.0017)
SEC	0.0082*	0.041***	0.0602***	0.0572***	0.0159**	0.0613***	0.0792***	0.0774***
	(0.0063)	(0.0043)	(0.0048)	(0.0062)	(0.0069)	(0.005)	(0.0056)	(0.006)
TOP5l					0.8021***	0.7405***	0.7196***	0.729***
					(0.0225)	(0.0182)	(0.015)	(0.0163)
TRD	-0.0236***	-0.0065***	-0.0025**	-0.002	-0.0299***	-0.0119***	-0.0076***	-0.0078***
	(0.0025)	(0.0013)	(0.0011)	(0.0017)	(0.0032)	(0.0013)	(0.0013)	(0.0017)
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes
J statistic	0.0985	0.1101	0.1101	0.1101	0.101	0.1101	0.1101	0.1101
J p-val	1	1	1	1	1	1	1	1
n mom	749	1015	1015	1185	749	1015	1015	1185
R^2 adj	0.9933	0.9932	0.9928	0.9924	0.9789	0.9791	0.9787	0.978
n total	1644	1562	1562	1562	1644	1562	1562	1562
n unique	87	86	86	86	87	86	86	86
average GI				3.355				3.355
average inequality lagged	54.4959	54.3621	54.3621	54.3621	31.8819	31.7725	31.7725	31.7725
average effect (×100)	0.0582	0.1082	0.1313	0.1219	0.1961	0.2674	0.2847	0.2931
SE	0.0004	0.0002	0.0003	0.0004	0.0005	0.0003	0.0003	0.0003
p-val	0.0615	0	0	0.0014	0.0001	0	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$

Table 11: The table presents results on the baseline regression (1.3) for other top income shares, restricted Gini coefficients, and absolute top incomes. The restricted Gini coefficient ($GINIy$) based on (Aghion et al., 2019) corresponds to the Gini coefficient computed on the bottom y% of the income distribution.

	top income shares			restricted Gini coefficients			absolute incomes		
	TOP10	TOP1	TOP01	G90	G95	G99	TOP10a	TOP1a	TOP01a
CO2	-1.1316***	-1.5789***	-0.3943***	0.0283***	0.0208***	0.0146***	0.0099*	-0.0708***	-0.138***
	(0.1277)	(0.1332)	(0.078)	(0.0021)	(0.0016)	(0.0015)	(0.0076)	(0.0097)	(0.0255)
GDP	-0.0593***	-0.0326***	0.0304***	-0.0003***	-0.0003***	-0.0004***	-0.0006***	0.0006**	0.0071***
	(0.0045)	(0.0043)	(0.0021)	(0)	(0)	(0)	(0.0003)	(0.0003)	(0.0006)
GF	0.6467***	0.4754***	0.0783*	0.0113***	0.0086***	0.0039***	0.5752***	0.918***	1.4619***
	(0.1244)	(0.0914)	(0.0511)	(0.001)	(0.0011)	(0.0013)	(0.0378)	(0.0483)	(0.0668)
GF_GINI90l				-0.0642***					
				(0.0055)					
GF_GINI95l					-0.0291***				
					(0.0034)				
GF_GINI99l						-0.0074***			
						(0.003)			
GF_TOP01al									-0.1039***
									(0.0047)
GF_TOP01l			-0.0179**						
			(0.0086)						
GF_TOP10al							-0.0482***		
							(0.0033)		
GF_TOP10l	-0.0092***								
	(0.0031)								
GF_TOP1al								-0.0698***	
								(0.0038)	
GF_TOP1l		-0.0198***							
		(0.0057)							
GINI90l				0.7251***					
				(0.0248)					
GINI95l					0.8589***				
					(0.0157)				
GINI99l						0.8256***			
						(0.0161)			
GOV	-0.0201	-0.132***	-0.0511***	-0.0005**	-0.0009***	-0.0017***	-0.0061***	-0.0124***	-0.014***
	(0.0244)	(0.026)	(0.0135)	(0.0002)	(0.0002)	(0.0002)	(0.0014)	(0.0023)	(0.0032)
INFL	0.0972***	0.0743***	0.0025	-0.0001	0.0009***	0.0016***	-0.0021**	-0.005***	-0.0087***
	(0.0147)	(0.017)	(0.0118)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0018)	(0.0027)
MCAP	0.1712***	0.3322***	-0.1123***	-0.0096***	-0.0099***	-0.0148***	-0.0416***	-0.0257***	0.0443***
	(0.0335)	(0.0523)	(0.0311)	(0.001)	(0.0009)	(0.0009)	(0.0042)	(0.0041)	(0.007)
PRIV	-0.0182***	-0.0177***	-0.0148***	-0.0001***	-0.0001***	0***	0.0005***	0.0006***	-0.0006***
	(0.0019)	(0.0015)	(0.001)	(0)	(0)	(0)	(0.0001)	(0.0001)	(0.0002)
SEC	0.0688***	0.091***	0.0435***	-0.0001***	0.0001***	0.0005***	0.0061***	0.0096***	0.0141***
	(0.0048)	(0.0044)	(0.0031)	(0)	(0)	(0)	(0.0003)	(0.0004)	(0.0007)
TOP01al									0.9305***
									(0.0149)
TOP01l			-0.0431						
			(0.0336)						
TOP10al							0.9446***		
							(0.006)		
TOP10l	0.7629***								
	(0.014)								
TOP1al								0.9394***	
								(0.009)	
TOP1l		0.4209***							
		(0.0264)							
TRD	-0.0076***	0.0016*	-0.0016*	0.0001***	0	0***	0.0003***	0.0002**	-0.001***
	(0.0018)	(0.0012)	(0.001)	(0)	(0)	(0)	(0.0001)	(0.0001)	(0.0002)
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
J statistic	0.1101	0.1101	0.1101	0.1101	0.1101	0.1101	0.1101	0.1101	0.1101
J p-val	1	1	1	1	1	1	1	1	1
n mom	1015	1015	1015	1015	1015	1015	1015	1015	1015
R^2 adj	0.9888	0.9063	0.554	0.9365	0.984	0.9872	0.9995	0.9992	0.9983
n total	1562	1562	1562	1562	1562	1562	1562	1562	1562
n unique	86	86	86	86	86	86	86	86	86
average inequality lagged	43.1213	15.1157	4.9651	0.2022	0.3371	0.4659	11.4751	12.6993	13.8533
average effect ($\times$100)	0.2501	0.1756	-0.0103	-0.0017	-0.0012	0.0004	0.0222	0.0317	0.0227
SE	0.0003	0.0004	0.0002	0	0	0	0	0	0
p-val	0	0	0.3268	0	0	0.0559	0	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.

Table 12: The table presents regression results for the baseline equation (1.3) for general investment effects. Specification TI regresses inequality on total investments, specification $TI|GI$ regresses inequality on total investments while controlling for green finance, and specification $TIz|GIz$ is similar to specification $TI|GI$ but uses the approach of standardized regression coefficients. Its advantage over using ordinary coefficients is the possibility to directly compare coefficient sizes.

	GINI			TOP_5		
specification	TI	TI|GI	TIz|GIz	TI	TI|GI	TIz|GIz
TI	4.8696**	2.4758**		4.7247**	2.4081**	
	(0.5198)	(0.5591)		(0.4999)	(0.4564)	
GI		-0.3461			-0.8373**	
		(0.5613)			(0.3992)	
TIz			0.0043			0.0806
			(0.0698)			(0.0711)
GIz			-0.0418**			-0.0461**
			(0.0217)			(0.0273)
INEQ lagged	0.8567**	0.6435**	0.5709**	0.5663**	0.3045**	0.4826**
	(0.0838)	(0.1064)	(0.0425)	(0.1602)	(0.164)	(0.0622)
TI x INEQ lagged	-0.0722**	-0.0095		-0.0691**	0.0176	
	(0.0146)	(0.0148)		(0.0226)	(0.0183)	
GI x INEQ lagged		0.0048			0.0218**	
		(0.0103)			(0.0125)	
TIz x INEQ lagged			-0.0934**			-0.1258**
			(0.0541)			(0.0729)
GIz x INEQ lagged			-0.0241**			-0.0003
			(0.0138)			(0.0205)
SEC	0.0425**	0.0583**	0.3065**	0.0187	0.0533**	0.3171**
	(0.0166)	(0.0146)	(0.0726)	(0.0252)	(0.0192)	(0.0675)
GOV	-0.3948**	0.0373	-0.5347**	-0.4907**	-0.0676	-0.5647**
	(0.0961)	(0.0744)	(0.0849)	(0.0773)	(0.0978)	(0.1066)
INFL	-0.0362	0.1088**	0.2465	0.0225	0.1803**	0.2987*
	(0.0602)	(0.063)	(0.2093)	(0.0564)	(0.0638)	(0.2146)
TRD	-0.0459**	-0.0264**	-0.1582**	-0.0645**	-0.0353**	-0.169**
	(0.0069)	(0.0067)	(0.0577)	(0.0082)	(0.0066)	(0.052)
MCAP	-0.1416	0.1317	-0.1217**	0.7767**	0.6586**	-0.0933
	(0.2213)	(0.1956)	(0.0591)	(0.2546)	(0.1818)	(0.0959)
GDP	-0.0356**	-0.1026**	-0.1179**	0.0125	-0.0785**	-0.1194**
	(0.0153)	(0.0186)	(0.0418)	(0.0172)	(0.0126)	(0.054)
PRIV	0.0203**	-0.0145**	-0.0043	0.0161**	-0.0221**	-0.0502**
	(0.0036)	(0.0034)	(0.0184)	(0.0036)	(0.0051)	(0.024)
CO2	0.5676	-0.6622	-0.1843	-0.5657	-1.3432*	-0.3018*
	(0.6417)	(0.6983)	(0.1865)	(0.7676)	(0.8353)	(0.1874)
time-specific effects	yes	yes	yes	yes	yes	yes
J statistic	0.0743	0.0887	0.0887	0.0743	0.0887	0.0887
J p-val	1	1	1	1	1	1
n mom	1020	1350	1350	1020	1350	1350
R^2 adj	0.9612	0.9864	0.8691	0.8356	0.9665	0.8256
n total	1507	1217	1217	1507	1217	1217
n unique	56	54	54	56	54	54
average inequality lagged	51.1021	50.9581	-0.7346	28.737	28.6315	-0.6886
average effect ($\times$100)	1.1719	1.9795	0.0725	2.7253	2.8982	0.1664
SE	0.005	0.0063	0.0007	0.0065	0.0067	0.0008
p-val	0.0097	0.0008	0.1437	0	0	0.0191

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.
Table-specific notes: The average effect is computed w.r.t. total investments and not w.r.t. green finance.

Table 13: The table presents regression results for the baseline equation (1.3) for renewable energy transactions (RETs) to address green washing concerns of the green finance indicator GI. RETs are classified into three investment types: acquisition, refinance, and new investment. The variable RET includes all investment types while the variable $RETi$ adjusts for greenwashing by considering new investments only. The baseline regression (1.3) is run for both variables consecutively.

	GINI		TOP_5	
	RET	RETi	RET	RETi
RET	-0.4029**		0.2668*	
	(0.1503)		(0.1701)	
RETi		0.0275		0.4646**
		(0.1692)		(0.1868)
INEQ lagged	0.8869**	0.9126**	0.7057**	0.8185**
	(0.0081)	(0.008)	(0.0202)	(0.0176)
RET x INEQ lagged	0.0101**		-0.0008	
	(0.0028)		(0.0051)	
RETi x INEQ lagged		0.0032		-0.0047
		(0.0031)		(0.0054)
SEC	0.0516**	0.032**	0.0723**	0.0573**
	(0.0038)	(0.0047)	(0.0062)	(0.0085)
GOV	0.169**	0.108**	0.2802**	0.1225**
	(0.0147)	(0.0197)	(0.03)	(0.0311)
INFL	0.0927**	0.0567**	0.0959**	0.022
	(0.0162)	(0.0198)	(0.0228)	(0.0248)
TRD	0.0032**	0.0177**	0.0107**	0.0293**
	(0.0014)	(0.0021)	(0.0025)	(0.0023)
MCAP	-0.1606**	0.1058**	-0.4567**	0.2481**
	(0.0451)	(0.0453)	(0.0864)	(0.0676)
GDP	-0.0331**	-0.0838**	-0.0742**	-0.1178**
	(0.0038)	(0.009)	(0.007)	(0.0108)
PRIV	-0.0127**	-0.0018	-0.021**	-0.0109**
	(0.0015)	(0.0015)	(0.0029)	(0.0022)
CO2	-0.768**	-0.2917**	-1.0813**	-0.8211**
	(0.082)	(0.1193)	(0.1247)	(0.1582)
time-specific effects	yes	yes	yes	yes
J statistic	0.1188	0.1281	0.1188	0.1281
J p-val	1	1	1	1
n mom	896	896	896	896
R^2 adj	0.9955	0.9958	0.97	0.9801
n total	1212	1046	1212	1046
n unique	72	67	72	67
average inequality lagged	53.6823	53.4793	31.1998	30.9881
average effect (×100)	0.1404	0.1999	0.2395	0.3165
SE	0.0001	0.0002	0.0002	0.0003
p-val	0	0	0	0

$^*p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.
Table-specific notes: The average effect is computed w.r.t. renewable energy transactions (RET or $RETi$) and not w.r.t. green finance.

Table 14: The table presents the regression results for the baseline equation (1.3) for the Gini coefficient ($GINI$) and the top 5% income share (TOP_5) for the subsample of countries in the OECD and the subsample of countries not in the OECD.

	GINI		TOP_5	
	OECD	non-OECD	OECD	non-OECD
GI	0.9717	2.536**	0.3049	2.1047**
	(0.9687)	(0.259)	(0.6604)	(0.1799)
INEQ lagged	0.8107**	0.9017**	0.7073**	0.7523**
	(0.0977)	(0.0132)	(0.1146)	(0.025)
GI x INEQ lagged	-0.017	-0.0387**	-0.0053	-0.0513**
	(0.0189)	(0.0044)	(0.023)	(0.0049)
SEC	0.0896**	0.0416**	0.1189**	0.0669**
	(0.02)	(0.0064)	(0.0237)	(0.0099)
GOV	-0.2746**	0.3814**	-0.297**	0.4474**
	(0.1191)	(0.0351)	(0.1172)	(0.0562)
INFL	0.3195**	0.0491**	0.2961**	0.0619**
	(0.1273)	(0.0164)	(0.1065)	(0.0156)
TRD	-0.0281**	-0.0069**	-0.0351**	-0.0018
	(0.0088)	(0.0026)	(0.0108)	(0.0031)
MCAP	-0.0006	0.0419	0.6922**	0.0648
	(0.3511)	(0.0352)	(0.3832)	(0.0604)
GDP	-0.0466**	0.2476**	-0.0519**	0.1966**
	(0.0161)	(0.0213)	(0.0202)	(0.0211)
PRIV	0.0045	-0.0557**	-0.0025	-0.0518**
	(0.0039)	(0.0037)	(0.0039)	(0.0034)
CO2	0.9725	-2.1267**	0.5502	-2.241**
	(0.9288)	(0.2077)	(1.0406)	(0.274)
time-specific effects	yes	yes	yes	yes
J statistic	0.0831	0.1632	0.0831	0.1632
J p-val	1	1	1	1
n mom	986	886	986	886
R^2 adj	0.9914	0.991	0.9716	0.9684
n total	866	674	866	674
n unique	36	55	36	55
average inequality lagged	47.6761	58.2333	26.1807	35.3497
average effect ($\times$100)	0.1624	0.2794	0.1655	0.2893
SE	0.0014	0.0003	0.0014	0.0004
p-val	0.1274	0	0.1141	0
mean PRIV	94.5223	57.2485	94.5223	57.2485
mean GDP	38.2883	8.7425	38.2883	8.7425
mean CO2	2.0498	0.8411	2.0498	0.8411

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.
Table-specific notes: The OECD membership is determined based on the OECD's categorization[21] of countries. Countries that enter the OECD between 2004 and 2020 will be categorized as OECD members from their entry year onward. For example, Slovenia joined the OECD on 21st of July in 2010, and hence, will be categorized as a non OECD member from 2004 to 2009 and as an OECD member from 2010 to 2020. "mean PRIV" gives the average financial development value, "mean GDP" the average income level, and "mean CO2" the average per capita carbon emissions. We include these number to provide the reader with some intuition on the difference in country characteristics between the OECD and non-OECD groups.

Table 15: The table presents the regression results for the baseline equation (1.3) for TOP_5 for country subsamples based on different initial country characteristics. The initial levels of a variable correspond to its first recorded values starting from 2004 for every country and represent the initial state condition of the countries. We use either financial development, measured via private credit ($PRIV$), the gross domestic product (GDP), or the per capita carbon dioxide emission level ($CO2$) as country characteristic. The variable is then split into its tertiles and we use the tertile's threshold values to assign countries to the low, moderate, or high initial level group.

	TOP_5								
country characteristic	PRIV			GDP			CO2		
tertile	high	middle	low	high	middle	low	high	middle	low
GI	0.7075**	0.6402	0.9055	0.3051	0.7069	1.7933**	0.7745	-0.0678	2.0233*
	(0.4059)	(1.3333)	(1.0536)	(1.1392)	(0.9795)	(0.9721)	(1.2881)	(0.6186)	(1.323)
$GI \times TOP_5$ *lagged*	-0.0129	-0.0195	-0.0188	0.0012	-0.0121	-0.0544**	-0.0202	0.0023	-0.0548*
	(0.013)	(0.0397)	(0.0295)	(0.0432)	(0.0297)	(0.0272)	(0.0459)	(0.0213)	(0.0341)
control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
R^2 adj	0.9728	0.9495	0.983	0.8992	0.9763	0.9882	0.9533	0.9737	0.983
n total	706	486	362	680	596	278	636	566	352
n unique	32	27	27	29	30	27	28	31	27
average effect (×100)	0.3451	0.0295	0.2613	0.3332	0.2938	-0.1124	0.2488	0.0016	-0.0857
p-val	0.0143	0.4506	0.0154	0.1778	0.0029	0.0449	0.1483	0.4945	0.1767
mean initial value	96.5534	38.3666	12.6803	24.4995	4.1884	0.6807	2.3821	1.5741	-0.4376

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$ *General notes*: see Appendix C. *Table-specific notes*: The "mean initial value" gives the average initial $PRIV$, GDP, or $CO2$ level in each of the thee groups (high, middle, low) of the corresponding variable.

Table 16: The table presents the regression results for the baseline equation (1.3) for $GINI$ for country subsamples based on different initial country characteristics. The initial levels of a variable correspond to its first recorded values starting from 2004 for every country and represent the initial state condition of the countries. We use either financial development, measured via private credit ($PRIV$), the gross domestic product (GDP), or the per capita carbon dioxide emission level ($CO2$) as country characteristic. The variable is then split into its tertiles and we use the tertile's threshold values to assign countries to the low, moderate, or high initial level group.

initial variable	PRIV			GDP			CO2		
tertile	high	middle	low	high	middle	low	high	middle	low
GI	0.8674*	0.7412	2.4913**	0.1791	2.4231**	3.192**	0.5486	1.2137	2.4709**
	(0.6749)	(1.9341)	(1.0428)	(1.3254)	(1.1812)	(1.5527)	(1.6062)	(1.0422)	(1.2725)
GINI lagged	0.9264**	0.6096**	0.8927**	0.6585**	0.9051**	0.8759**	0.7105**	0.7431**	0.89**
	(0.0786)	(0.1586)	(0.0659)	(0.18)	(0.0542)	(0.0901)	(0.1362)	(0.0777)	(0.0688)
GI x GINI lagged	-0.0094	-0.0182	-0.0409**	0.0045	-0.04**	-0.056**	-0.0076	-0.0259*	-0.0424**
	(0.0115)	(0.0351)	(0.018)	(0.0261)	(0.0212)	(0.0265)	(0.0319)	(0.0197)	(0.0203)
SEC	0.0314**	0.019	0.1**	0.0352	0.1195**	0.0581**	0.0527*	-0.0037	0.0372**
	(0.0172)	(0.0449)	(0.0273)	(0.0437)	(0.0377)	(0.0176)	(0.0381)	(0.0375)	(0.01)
GOV	0.3423**	0.3154	0.1913**	0.5591**	0.0572	0.2433**	-0.0588	-0.0414	0.09*
	(0.1022)	(0.2656)	(0.0921)	(0.2092)	(0.1499)	(0.0829)	(0.1922)	(0.134)	(0.0582)
INFL	0.0716	0.1106	0.0413	0.1745	0.0051	0.1004**	0.1573	0.0483	-0.0681**
	(0.211)	(0.0959)	(0.0654)	(0.3064)	(0.141)	(0.0364)	(0.2416)	(0.0706)	(0.0337)
TRD	0.0077**	0.0051	-0.0126	0.0218**	-0.0202	0.0051	-0.0011	-0.0209**	0.0368**
	(0.0045)	(0.0163)	(0.0114)	(0.0112)	(0.0214)	(0.0119)	(0.0112)	(0.0097)	(0.0163)
MCAP	1.2487**	-0.5776**	-0.1557	1.0645	-0.0849	0.1408	-1.6578**	0.4098*	-0.0154
	(0.4625)	(0.3379)	(0.1589)	(0.9566)	(0.1939)	(0.1513)	(0.5324)	(0.3054)	(0.2137)
GDP	0.0038	0.0176	-0.3459**	0.0831**	-0.3231**	-0.2185	0.0149	-0.1108**	-0.1817**
	(0.0201)	(0.0856)	(0.1006)	(0.0406)	(0.1462)	(0.1736)	(0.0167)	(0.0321)	(0.0745)
PRIV	-0.002	-0.0347*	-0.1131**	-0.0167*	-0.0842**	-0.012	-0.0431**	-0.0034	0.0565**
	(0.0058)	(0.024)	(0.0331)	(0.0113)	(0.0215)	(0.0125)	(0.0116)	(0.0105)	(0.0201)
CO2	-5.0039**	-1.4002*	-0.3676	-2.3554	-0.1851	-1.3327**	-1.058	6.9637**	-0.9877**
	(1.4344)	(0.9838)	(0.5109)	(2.3412)	(1.2344)	(0.33)	(1.9494)	(1.7899)	(0.423)
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
J statistic	0.0907	0.1111	0.1492	0.0853	0.1007	0.1942	0.0881	0.1095	0.1534
J p-val	1	1	1	1	1	1	1	1	1
n mom	986	990	880	986	880	886	968	986	880
R^2 adj	0.9927	0.9799	0.9955	0.9777	0.9896	0.9964	0.9874	0.9853	0.9972
n total	706	486	362	680	596	278	636	566	352
n unique	32	27	27	29	30	27	28	31	27
average inequality lagged	50.0355	53.0708	57.0717	46.9391	56.5679	57.4249	47.7162	52.348	61.3978
average effect (×100)	0.3935	-0.2223	0.1567	0.3873	0.1586	-0.0221	0.1827	-0.1404	-0.1302
SE	0.0019	0.0028	0.0009	0.0036	0.0011	0.0009	0.002	0.0013	0.0005
p-val	0.0204	0.2128	0.0399	0.1428	0.0713	0.3983	0.1814	0.137	0.0084
mean initial value	96.5534	38.3666	12.6803	24.4995	4.1884	0.6807	2.3821	1.5741	-0.4376

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.
Table-specific notes: The "mean initial value" gives the average initial $PRIV$, GDP, or $CO2$ level in each of the thee groups (high, middle, low) of the corresponding variable.

Table 17: The table presents the regression results for the baseline equation (1.3) for TOP_5 for country subsamples based on different initial country characteristics. The initial levels of a variable correspond to its first recorded values starting from 2004 for every country and represent the initial state condition of the countries. We use either financial development, measured via private credit ($PRIV$), the gross domestic product (GDP), or the per capita carbon dioxide emission level ($CO2$) as country characteristic. The variable is then split into its tertiles and we use the tertile's threshold values to assign countries to the low, moderate, or high initial level group.

initial variable	PRIV			GDP			CO2		
tertile	high	middle	low	high	middle	low	high	middle	low
GI	0.7075**	0.6402	0.9055	0.3051	0.7069	1.7933**	0.7745	-0.0678	2.0233*
	(0.4059)	(1.3333)	(1.0536)	(1.1392)	(0.9795)	(0.9721)	(1.2881)	(0.6186)	(1.323)
TOP_5 lagged	0.782**	0.4951**	0.7329**	0.2852	0.8111**	0.7656**	0.4794**	0.6973**	0.6365**
	(0.1068)	(0.1241)	(0.0874)	(0.3121)	(0.0895)	(0.0618)	(0.1703)	(0.0765)	(0.0877)
GI x TOP_5 lagged	-0.0129	-0.0195	-0.0188	0.0012	-0.0121	-0.0544**	-0.0202	0.0023	-0.0548*
	(0.013)	(0.0397)	(0.0295)	(0.0432)	(0.0297)	(0.0272)	(0.0459)	(0.0213)	(0.0341)
SEC	0.0605**	0.0166	0.1355**	0.0502	0.1429**	0.0521**	0.0445	0.0742**	0.0702**
	(0.0277)	(0.0346)	(0.0447)	(0.0483)	(0.0514)	(0.0139)	(0.0425)	(0.042)	(0.0254)
GOV	0.2684**	0.3518**	0.3551**	0.4149**	-0.0904	0.2462**	-0.0935	0.0294	0.2193**
	(0.1401)	(0.2106)	(0.1177)	(0.2004)	(0.1491)	(0.067)	(0.2075)	(0.1331)	(0.1231)
INFL	0.0742	0.0694	0.0288	0.1966	0.0674	0.1063**	0.0887	0.0324	-0.0904*
	(0.1887)	(0.0811)	(0.0695)	(0.391)	(0.134)	(0.0298)	(0.268)	(0.0707)	(0.0556)
TRD	0.005	0.0058	-0.0133	0.0262**	-0.0238	0.0059	-0.0113	-0.0132*	0.0525**
	(0.0056)	(0.0261)	(0.0139)	(0.0115)	(0.0207)	(0.0113)	(0.0127)	(0.0088)	(0.0234)
MCAP	1.3596**	-0.0192	-0.3715	1.321	0.015	0.0716	-1.4546**	0.914**	-0.3408
	(0.5072)	(0.4212)	(0.3355)	(1.2128)	(0.2101)	(0.1234)	(0.5113)	(0.3604)	(0.337)
GDP	-0.0025	-0.0032	-0.399**	0.1103**	-0.1012	-0.089	0.0242	-0.1015**	-0.1528
	(0.0266)	(0.0725)	(0.1313)	(0.0392)	(0.1706)	(0.2129)	(0.019)	(0.022)	(0.1195)
PRIV	-0.0109**	-0.0403	-0.1265**	-0.0143*	-0.0659**	0.0076	-0.0462**	-0.0191**	0.0852**
	(0.0051)	(0.0385)	(0.0464)	(0.011)	(0.0199)	(0.0133)	(0.0131)	(0.0095)	(0.0298)
CO2	-3.9879**	-2.8941**	-1.046*	-1.0981	-0.289	-1.7707**	1.1922	1.9995*	-2.1646**
	(1.3664)	(1.196)	(0.6456)	(2.7797)	(1.2484)	(0.3899)	(2.0688)	(1.5251)	(0.618)
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
J statistic	0.0907	0.1111	0.1492	0.0853	0.1007	0.1942	0.0881	0.1095	0.1534
J p-val	1	1	1	1	1	1	1	1	1
n mom	986	990	880	986	880	886	968	986	880
R^2 adj	0.9728	0.9495	0.983	0.8992	0.9763	0.9882	0.9533	0.9737	0.983
n diff	353	243	181	340	298	139	318	283	176
n level	353	243	181	340	298	139	318	283	176
n total	706	486	362	680	596	278	636	566	352
n unique	32	27	27	29	30	27	28	31	27
average inequality lagged	27.9474	31.2689	34.2856	25.1385	34.1023	35.0603	25.9211	30.2561	38.514
average effect ($\times 100$)	0.3451	0.0295	0.2613	0.3332	0.2938	-0.1124	0.2488	0.0016	-0.0857
SE	0.0016	0.0024	0.0012	0.0036	0.0011	0.0007	0.0024	0.0011	0.0009
p-val	0.0143	0.4506	0.0154	0.1778	0.0029	0.0449	0.1483	0.4945	0.1767
mean initial value	96.5534	38.3666	12.6803	24.4995	4.1884	0.6807	2.3821	1.5741	-0.4376

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.
Table-specific notes: The "mean initial value" gives the average initial $PRIV$, GDP, or $CO2$ level in each of the thee groups (high, middle, low) of the corresponding variable.

Table 18: Results for the time-delayed regression equation (2) for the Gini coefficient ($GINI$) and the top 5% income share (TOP_5). Green finance enters the equation with lag $z \in \{0, 2, 4, 6\}$. Due to space reasons, we provide the output for even lags only.

	GINI				TOP_5			
lag z	0	2	4	6	0	2	4	6
GI z	1.0983**	2.0718**	1.3289**	-0.8429**	0.8642**	1.9509**	1.2354**	-0.0562
	(0.1686)	(0.2764)	(0.3439)	(0.4889)	(0.1291)	(0.231)	(0.2721)	(0.2838)
INEQ z=1	0.7835**	0.6525**	0.6694**	0.377**	0.7196**	0.4009**	0.3502**	-0.0747
	(0.0148)	(0.036)	(0.0419)	(0.0586)	(0.015)	(0.0316)	(0.0482)	(0.0649)
INEQ z+1		0.2907**	0.1962**	0.4083**		0.5499**	0.3796**	0.6371**
		(0.0418)	(0.0505)	(0.0596)		(0.0486)	(0.0604)	(0.058)
GI z x INEQ z+1	-0.0178**	-0.043**	-0.0325**	0.0035	-0.0182**	-0.0727**	-0.0496**	-0.0207**
	(0.0031)	(0.0052)	(0.0064)	(0.0097)	(0.0042)	(0.0076)	(0.0078)	(0.0105)
SEC	0.0602**	0.0209**	0.0601**	0.1092**	0.0792**	0.0309**	0.0803**	0.1401**
	(0.0048)	(0.0085)	(0.0107)	(0.0136)	(0.0056)	(0.0136)	(0.0136)	(0.0215)
GOV	-0.0134	-0.4244**	-0.0678	0.5751**	-0.1283**	-0.592**	-0.283**	0.3057**
	(0.0191)	(0.0486)	(0.0619)	(0.0962)	(0.0256)	(0.0554)	(0.0744)	(0.1313)
INFL	0.1093**	0.3155**	0.1334**	0.2446**	0.0859**	0.2445**	0.1962**	0.1656**
	(0.0145)	(0.0286)	(0.0492)	(0.0769)	(0.0241)	(0.0416)	(0.0591)	(0.0965)
TRD	-0.0025**	-0.0093**	-0.0402**	-0.0437**	-0.0076**	-0.0063*	-0.0296**	-0.0013
	(0.0011)	(0.0039)	(0.0064)	(0.0077)	(0.0013)	(0.0042)	(0.0061)	(0.0085)
MCAP	0.0363**	-1.6507**	1.1422**	0.2222	0.2466**	-2.0151**	1.6083**	-0.2743
	(0.0188)	(0.1425)	(0.1961)	(0.2041)	(0.0426)	(0.2018)	(0.2382)	(0.2542)
GDP	-0.066**	-0.0048	-0.0432**	0.0085	-0.0648**	0.0463**	0.0135	0.0165
	(0.0033)	(0.0081)	(0.0102)	(0.0164)	(0.0045)	(0.0086)	(0.0141)	(0.0169)
PRIV	-0.014**	-0.0013	0.0056	-0.064**	-0.0186**	-0.0059**	0.0181**	-0.0448**
	(0.0012)	(0.003)	(0.0061)	(0.0089)	(0.0017)	(0.0024)	(0.0073)	(0.0102)
CO2	-0.9958**	3.3851**	2.6592**	0.0075	-1.075**	2.2949**	0.9522**	-2.3678**
	(0.1202)	(0.3643)	(0.4664)	(0.4472)	(0.1387)	(0.3356)	(0.5107)	(0.6353)
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes
J statistic	0.1101	0.0892	0.1027	0.114	0.1101	0.0909	0.1049	0.1103
J p-val	1	1	1	1	1	1	1	1
n mom	1015	540	416	308	1015	540	416	308
R^2 adj	0.9928	0.9867	0.9814	0.9774	0.9787	0.958	0.9222	0.9259
n total	1562	1433	1215	987	1562	1433	1215	987
n unique	86	82	78	71	86	82	78	71

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.

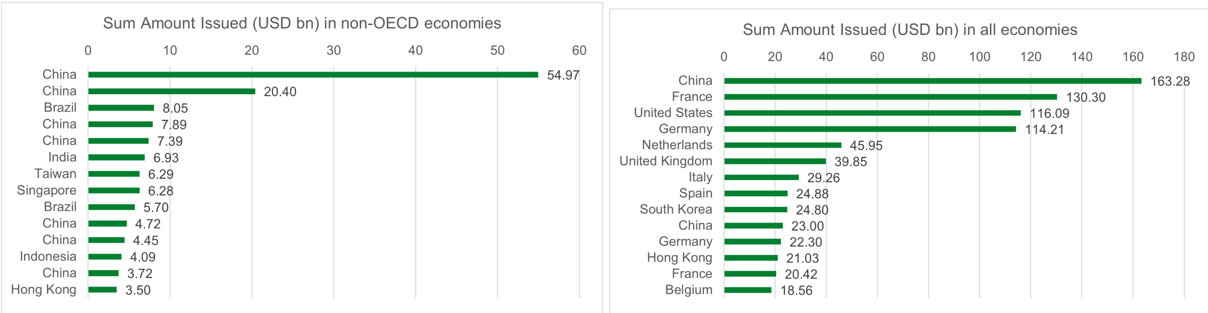
E Robustness Results

Table 19: Regression results for equation (1.3) with CSR or TXR instead of $CO2$ for the Gini coefficient and the top 5% income share.

	GINI		TOP_5	
additional control	CSR	TXR	CSR	TXR
CSR	0.8226***		1.0631***	
	(0.105)		(0.1446)	
GDP	-0.0831***	-0.0405***	-0.0889***	-0.0702***
	(0.0053)	(0.0067)	(0.0082)	(0.0064)
GF	1.0208***	1.7401***	0.7776***	2.264***
	(0.1785)	(0.1511)	(0.1547)	(0.1459)
GF_GINIl	-0.0172***	-0.0271***		
	(0.0034)	(0.0027)		
GF_TOP5l			-0.0174***	-0.0554***
			(0.005)	(0.0042)
GINIl	0.7725***	0.9213***		
	(0.0159)	(0.0115)		
GOV	-0.093***	0.2834***	-0.2325***	0.0258
	(0.018)	(0.0311)	(0.0289)	(0.034)
INFL	0.108***	0.2004***	0.0797***	0.1321***
	(0.0131)	(0.0299)	(0.0252)	(0.0293)
MCAP	-0.0145	0.0117	0.185***	0.2965***
	(0.0352)	(0.046)	(0.0511)	(0.0564)
PRIV	-0.0157***	-0.0248***	-0.0205***	-0.0189***
	(0.0013)	(0.0022)	(0.0017)	(0.0023)
SEC	0.0231***	0.0159***	0.0368***	0.0087**
	(0.0046)	(0.0039)	(0.0049)	(0.0047)
TOP5l			0.6981***	1.0012***
			(0.0174)	(0.0186)
TRD	-0.0125***	-0.0037*	-0.0199***	-0.0113***
	(0.0013)	(0.0023)	(0.002)	(0.0024)
TXR		-0.0027***		-0.0003
		(0.0003)		(0.0004)
time-specific effects	yes	yes	yes	yes
J statistic	0.1101	0.1396	0.1101	0.1432
J p-val	1	1	1	1
n mom	1015	390	1015	390
R^2 adj	0.9922	0.991	0.9763	0.9713
n total	1562	942	1562	942
n unique	86	71	86	71
average INEQ lagged	54.3621	53.4644	31.7725	31.066
average effect (×100)	0.107	0.3241	0.2411	0.5306
SE	0.0003	0.0004	0.0004	0.0005
p-val	0.0002	0	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$

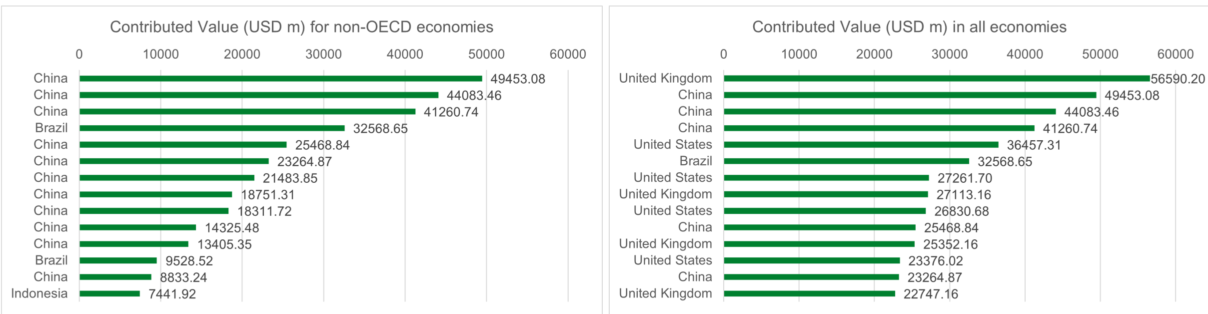
General notes: see Appendix C.



(a) non-OECD sample

(b) full sample

Figure 10: Figures 10a and 10b show for the non-OECD resp. full sample the corresponding country of the top 15 issuers of green debt (GD) based on a descending ordered list of the issuers' total issuance amount. Due to data privacy, we only show the country of the issuer but not the name of the issuer.



(a) non-OECD sample

(b) full sample

Figure 11: Figures 10a and 10b show for the non-OECD resp. full sample the corresponding country of the top 15 countries of renewable energy transactions (RET) based on a descending ordered list of the companies' total investment amount. Due to data privacy, we only show the country of the company but not the name of the company.

Table 20: Regression results for equation (1.3) with RLI, PRI, GEI, and CCI as institutional quality controls for the Gini coefficient and the top 5% income share.

	GINI				TOP_5			
additional control	RLI	PRI	GEI	CCI	RLI	PRI	GEI	CCI
CCI				-0.8861***				-0.6189***
				(0.1073)				(0.1287)
CO2	-1.1171***	-1.0471***	-0.9308***	-1.1408***	-1.0644***	-1.1854***	-0.8261***	-1.1022***
	(0.1258)	(0.1467)	(0.1924)	(0.1316)	(0.1868)	(0.1563)	(0.1671)	(0.1738)
GDP	-0.0484***	-0.0589***	-0.0517***	-0.0553***	-0.0409***	-0.0579***	-0.0421***	-0.057***
	(0.0046)	(0.0038)	(0.0048)	(0.0043)	(0.0059)	(0.0043)	(0.0047)	(0.0053)
GEI			-2.1785***				-2.7091***	
			(0.2277)				(0.2194)	
GF	0.8903***	1.186***	0.9635***	0.9911***	0.7148***	0.9395***	0.7725***	0.8434***
	(0.188)	(0.2018)	(0.196)	(0.164)	(0.1326)	(0.1281)	(0.1241)	(0.1375)
GF_GINIl	-0.0135***	-0.0206***	-0.0146***	-0.0154***				
	(0.0037)	(0.0038)	(0.0039)	(0.0031)				
GF_TOP5l					-0.0129***	-0.0224***	-0.0139***	-0.0172***
					(0.0046)	(0.0043)	(0.0042)	(0.0043)
GINIl	0.7563***	0.7841***	0.7646***	0.7668***				
	(0.0164)	(0.018)	(0.0192)	(0.0164)				
GOV	-0.0141	0.0053	-0.0107	-0.0139	-0.1243***	-0.1214***	-0.086***	-0.1304***
	(0.0228)	(0.0224)	(0.0269)	(0.0182)	(0.0309)	(0.0245)	(0.0321)	(0.0308)
INFL	0.1127***	0.1033***	0.1049***	0.1108***	0.0898***	0.081***	0.0749***	0.0873***
	(0.0132)	(0.015)	(0.0112)	(0.0137)	(0.0218)	(0.0251)	(0.0176)	(0.0208)
MCAP	0.0446*	0.1148***	0.0685**	0.0293*	0.2565***	0.3177***	0.2728***	0.2379***
	(0.0319)	(0.0337)	(0.0348)	(0.0228)	(0.0616)	(0.042)	(0.0414)	(0.055)
PRI		0.025***				0.026***		
		(0.004)				(0.0047)		
PRIV	-0.0076***	-0.0223***	-0.0014	-0.0078***	-0.0119***	-0.025***	-0.007***	-0.0153***
	(0.0011)	(0.0015)	(0.0011)	(0.0009)	(0.0019)	(0.002)	(0.0018)	(0.0016)
RLI	-1.4435***				-1.9594***			
	(0.1544)				(0.2103)			
SEC	0.0778***	0.0529***	0.0777***	0.0698***	0.0949***	0.072***	0.0897***	0.0838***
	(0.0061)	(0.0052)	(0.0061)	(0.0057)	(0.0053)	(0.0052)	(0.0047)	(0.0052)
TOP5l					0.6747***	0.7235***	0.7001***	0.7062***
					(0.0217)	(0.0163)	(0.0204)	(0.0193)
TRD	-0.0005	-0.0049***	0.0023*	0.0001	-0.0055***	-0.01***	-0.0032**	-0.0061***
	(0.0013)	(0.0011)	(0.0016)	(0.0011)	(0.0016)	(0.0018)	(0.0016)	(0.0013)
time-specific effects	yes	yes	yes	yes	yes	yes	yes	yes
J statistic	0.1101	0.109	0.1101	0.1101	0.1101	0.109	0.1101	0.1101
J p-val	1	1	1	1	1	1	1	1
n mom	1015	1015	1015	1015	1015	1015	1015	1015
R^2 adj	0.9923	0.9927	0.992	0.9924	0.9766	0.9784	0.9766	0.9782
n total	1562	1560	1562	1562	1562	1560	1562	1562
n unique	86	85	86	86	86	85	86	86
average INEQ lagged	54.3621	54.3354	54.3621	54.3621	31.7725	31.7609	31.7725	31.7725
average effect ($\times$100)	0.1537	0.068	0.1692	0.1552	0.3044	0.2284	0.33	0.2952
SE	0.0004	0.0004	0.0003	0.0003	0.0003	0.0003	0.0004	0.0004
p-val	0	0.0284	0	0	0	0	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.

Table 21: Regression results for equation (1.3) for the Gini coefficient and the top 5% income share with unemployment as an additional control.

	GINI	TOP5
CO2	-1.1651***	-1.2207***
	(0.1477)	(0.1565)
GDP	-0.071***	-0.0692***
	(0.0045)	(0.0046)
GF	1.0339***	0.8325***
	(0.1594)	(0.1496)
GF_GINIl	-0.0168***	
	(0.003)	
GF_TOP5l		-0.0177***
		(0.0049)
GINIl	0.7714***	
	(0.0139)	
GOV	-0.0012	-0.113***
	(0.0251)	(0.0283)
INFL	0.1158***	0.0905***
	(0.0125)	(0.0183)
MCAP	0.0314	0.2282***
	(0.0293)	(0.0476)
PRIV	-0.0128***	-0.0181***
	(0.0011)	(0.0017)
SEC	0.0728***	0.089***
	(0.0055)	(0.006)
TOP5l		0.7095***
		(0.017)
TRD	-0.0032***	-0.0072***
	(0.0013)	(0.0017)
UNMP	-0.1018***	-0.1206***
	(0.0156)	(0.012)
time-specific effects	yes	yes
J statistic	0.1101	0.1101
J p-val	1	1
R^2 adj	0.9924	0.9781
n mom	1015	1015
n total	1562	1562
n unique	86	86
average INEQ lagged	54.3621	31.7725
average effect (×100)	0.1185	0.2681
SE	0.0003	0.0004
p-val	0	0

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.

Table 22: Regression results for equation (1.3) for the Gini coefficient and the top 5% income share with interest ($INTR$) as an additional control.

	GINI	TOP5
CO2	-1.1427***	-2.1149***
	(0.1586)	(0.35)
GDP	0.0194***	-0.0044
	(0.0076)	(0.015)
GF	0.4775*	0.9028***
	(0.3106)	(0.3847)
GF_GINIl	-0.0056	
	(0.0056)	
GF_TOP5l		-0.0184**
		(0.0108)
GINIl	0.9155***	
	(0.0141)	
GOV	0.1176***	0.3521***
	(0.0441)	(0.065)
INFL	0.0853***	0.0884***
	(0.0307)	(0.0371)
INTR	-0.0866***	-0.0934***
	(0.017)	(0.018)
MCAP	0.1314***	0.4039***
	(0.0503)	(0.0926)
PRIV	-0.0204***	-0.0502***
	(0.0027)	(0.0055)
SEC	0.0695***	0.1313***
	(0.0088)	(0.0171)
TOP5l		0.6891***
		(0.0401)
TRD	-0.0041**	0.0044
	(0.002)	(0.0039)
time-specific effects	yes	yes
J statistic	0.1278	0.1278
J p-val	1	1
n mom	903	903
R^2 adj	0.9949	0.9587
n total	892	892
n unique	57	57
average INEQ lagged	56.1104	33.5049
average effect ($\times 100$)	0.1637	0.2839
SE	0.0005	0.0005
p-val	0.0002	0

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.

Table 23: (1.3)

	GINI	TOP5
GF	0.9373***	0.7081***
	(0.1731)	(0.1445)
CO2	-0.9307***	-1.0482***
	(0.1063)	(0.1707)
GDP	-0.0599***	-0.0571***
	(0.0035)	(0.0051)
GF_GINIl	-0.0156***	
	(0.0032)	
GF_TOP5l		-0.0143***
		(0.0046)
GINIl	0.7709***	
	(0.0173)	
GOV	0.0055	-0.1185***
	(0.0214)	(0.0257)
INFL	0.1105***	0.0911***
	(0.0132)	(0.0219)
MCAP	0.0673**	0.2847***
	(0.0389)	(0.0464)
PRIV	-0.0206***	-0.0269***
	(0.0013)	(0.0018)
SEC	0.0561***	0.0798***
	(0.0048)	(0.0055)
TOP5l		0.7044***
		(0.0201)
TRD	-0.0009	-0.0052***
	(0.0012)	(0.0019)
J p-val	1	1
J statistic	0.1098	0.1098
R^2 adj	0.9927	0.9782
SE	0.0003	0.0004
average effect ($\times$100)	0.0895	0.2507
average inequality lagged	54.3952	31.8452
n diff	752	752
n level	760	760
n mom	1014	1014
n total	1512	1512
n unique	83	83
p-val	0.001	0

Table 24: no interaction term base regression for gini and top5

	GINI	TOP5
CO2	-1.0121***	-1.955***
	(0.2325)	(0.4645)
GDP	-0.0362***	-0.0202**
	(0.0065)	(0.0094)
GF	-0.0262	0.2476***
	(0.0509)	(0.0698)
GINIl	0.8154***	
	(0.0159)	
GOV	-0.1215***	-0.2695***
	(0.0392)	(0.0599)
INFL	0.1706***	0.1772***
	(0.0262)	(0.036)
MCAP	-0.3717***	-0.1708*
	(0.072)	(0.1127)
PRIV	0.005***	-0.0019
	(0.0019)	(0.0029)
SEC	0.1007***	0.1378***
	(0.0097)	(0.0165)
TOP5l		0.5927***
		(0.0324)
TRD	0.0052***	0.0161***
	(0.002)	(0.0038)
J p-val	1	1
J statistic	0.0924	0.0917
R^2 adj	0.993	0.9559
SE	0.0005	0.0007
average effect ($\times$100)	-0.0261	0.2464
average inequality lagged	54.3621	31.7725
n diff	777	777
n level	888	888
n mom	680	680
n total	1665	1665
n unique	86	86
p-val	0.3035	0.0002

Table 25: Initial value regressions for $GINITOP5$

	OECD	non-OECD	OECD	non-OECD
CO2	5.4864***	-2.7413***	4.5715***	-2.8021***
	(1.947)	(0.4826)	(1.7945)	(0.473)
GDP	0.0413*	0.5744***	0.0555***	0.538***
	(0.029)	(0.0335)	(0.0231)	(0.0456)
GF	0.0293	0.2357***	0.0645	0.2528**
	(0.3189)	(0.0869)	(0.2533)	(0.1138)
GINIl	0.2922***	0.5733***		
	(0.1228)	(0.0279)		
GOV	0.2091	0.8561***	0.0139	0.7601***
	(0.1774)	(0.0724)	(0.1388)	(0.0685)
INFL	0.2648	0.1099***	0.3039**	0.1061***
	(0.2218)	(0.0282)	(0.1653)	(0.0266)
MCAP	-0.4309	0.5857***	-0.3278	0.4481***
	(0.4429)	(0.0838)	(0.4405)	(0.0982)
PRIV	-0.0066	-0.0065	-0.011*	-0.0116*
	(0.0083)	(0.0084)	(0.0068)	(0.0077)
SEC	0.0969***	0.0856***	0.0798***	0.0997***
	(0.03)	(0.0098)	(0.0266)	(0.0115)
TOP5l			0.0528	0.3176***
			(0.1535)	(0.045)
TRD	0.0203**	0.0138**	0.0023	0.0127**
	(0.011)	(0.0064)	(0.0103)	(0.0065)
J p-val	1	1	1	1
J statistic	0.0831	0.1632	0.0831	0.1632
R^2 adj	0.9287	0.9329	0.7931	0.822
SE	0.0032	0.0009	0.0025	0.0011
average effect ($\times 100$)	0.0292	0.2345	0.0641	0.2515
average inequality lagged	47.6761	58.2333	26.1807	35.3497
mean CO2	2.0498	0.8411	2.0498	0.8411
mean GDP	38.2883	8.7425	38.2883	8.7425
mean PRIV	94.5223	57.2485	94.5223	57.2485
n diff	433	337	433	337
n level	433	337	433	337
n mom	663	595	663	595
n total	866	674	866	674
n unique	36	55	36	55
p-val	0.4634	0.0034	0.3996	0.0133

F Mediation Analysis

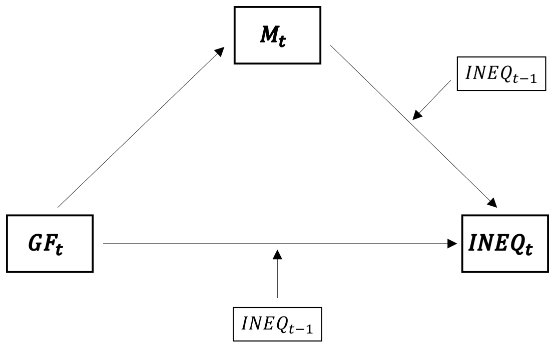


Figure 12: Graphical representation of the moderated mediation design. M is the mediator and lagged inequality ($INEQ_{t-1}$) the moderator. The effect of green finance (GI) on inequality ($INEQ$) is channeled through the mediator (M).

Investment emissions via capital formation. For a simple diagnostic insight into this chain of relationships, we run two simple regressions: capital formation on green finance, and investment emissions on capital formation. To measure capital formation empirically, we use data from the World Bank and use capital formation in percent of GDP[39]. The variable is denoted as CF. To capture investment emissions, we use data from WID[41] on the personal carbon footprint from investments in MtCO2e[40]. The estimates represent emissions from individual investments, which are emissions attributed to capital formation and firm ownership. Note that investment emissions do not encompass emissions associated with individual consumption and government expenditures. Due to large value differences between countries, we apply the natural logarithm to the data. The variable is denoted as IE. The regression results in table 28 indeed show a significant and positive association between green finance and capital formation, as well as a significant positive association between capital formation and investment emissions. We take these results as first evidence that an increase in green finance is linked to more investment emissions.

Carbon inequality To measure carbon inequality empirically, we use data from the WID[41] on the personal carbon footprint across all sectors in tCO2 equivalent per GDP[42]. The data provides a measure of the average emissions within a selected group for each country and year. The indicator captures emissions related to both individual consumption and government expenditures, as well as emissions associated with individuals' investments. The unit of measurement is based on individuals rather than households, assuming no resource sharing within couples. Based on this dataset we construct our main indicator, which is the average carbon footprint of the top 5% of emitters, denoted by CI. Table **??** displays the summary statistics for investment emissions and carbon inequality over the years 2004 to 2020.

Results. Table 29 presents the regression results of the moderated mediation analysis. The results on investment emissions confirm our earlier diagnostic regression, with green finance and investment emissions being significantly and positively associated. Moreover, investment emissions have a positive and significant effect on the Gini coefficient and the top 5% income share while the effect of green finance on these two inequality variables is greatly reduced and

[39] Source: https://data.worldbank.org/indicator/NE.GDI.TOTL.ZS, as of 01.06.2023. Gross capital formation consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and "work in progress".

[40] The WID variable identifier is *eifghgi999*.

[41] Source: https://wid.world/data/, as of 01.06.2023.

[42] The WID variable identifier is *lpfghgi999*.

turns negative. These results indicate that investment emissions indeed channel the positive association between green finance and income inequality. The results on carbon inequality reveal that there is also a positive and significant association between green finance and the carbon footprint of top emitters. This result implies that more green finance is associated with more carbon emission of the top emitters. Moreover, the carbon footprint of the top emitters is positively linked to inequality. The effect of green finance is clearly reduced in the presence of carbon inequality as the mediator. We take these results as first evidence for the existence of a transmitting effect of carbon emission levels on the relationship between green finance and inequality.

Table 26: This table gives the moderated mediation regression results for innovation (measured via green and general patents and denoted as $PATe$ resp. PAT), technological change (measured via research and development expenditures and denoted as RD), and employment in research, scientific and related fields, denoted as EMP. The mediator M is either $PATe$, PAT, RD, or EMP, and channels the effect of green finance on inequality.

equation	(3)	(4)	
outcome	$PATe$	$GINI$	TOP_5
mediator		PATe	PATe
CO2	1.1134***	1.0429***	1.1301***
	(0.4397)	(0.282)	(0.3422)
FDI	0.0069***	-0.0177***	-0.0278***
	(0.0009)	(0.0068)	(0.0093)
GDP	0.0018	-0.0736***	-0.0926***
	(0.0072)	(0.0087)	(0.0111)
GF	0.1058***	0.396	0.0171
	(0.0286)	(0.3698)	(0.2934)
GF_GINIl		-0.0048	
		(0.007)	
GF_TOP5l			0.0059
			(0.0091)
GINIl		0.8791***	
		(0.0323)	
GOV	0.0426	-0.4222***	-0.4903***
	(0.042)	(0.0579)	(0.0601)
INFL	-0.0787***	0.0521*	0.006
	(0.026)	(0.035)	(0.0473)
MCAP	-0.0215	-0.3122***	-0.6638***
	(0.1291)	(0.1282)	(0.2282)
PATe		1.5044***	0.9282***
		(0.299)	(0.2511)
PATe_GINIl		-0.028***	
		(0.0056)	
PATe_TOP5l			-0.029***
			(0.0073)
PRIV	-0.0027	-0.0041*	-0.0044
	(0.0029)	(0.0026)	(0.0043)
SEC	0.0057	0.0791***	0.099***
	(0.0069)	(0.0069)	(0.0075)
TOP5l			0.7884***
			(0.0391)
TRD	-0.0037	-0.0066**	-0.0066**
	(0.0035)	(0.0033)	(0.0039)
UNMP	-0.0075	0.0904***	0.1018***
	(0.022)	(0.0269)	(0.0386)
J p-val	1	1	1
J statistic	0.0862	0.1121	0.1121
R^2 adj	0.661	0.994	0.975
average INEQ lagged		51.7069	29.7505
direct average effect		0.1493	0.1912
indirect average effect		0.0001	0.0001
n diff	571	571	571
n level	571	571	571
n mom	270	927	927
n total	1142	1142	1142
n unique	64	64	64
total average effect		0.1494	0.1913

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. *General notes*: see Appendix C. [REMARK: link to full table in appendix]

Table 27: Moderated mediation results.

	PAT	RD	EMP48	PAT	RD	EMP48	PAT	RD	EMP48
GI	0.0848***	0.0154**	0.0412**	-1.3794***	-0.5331	-0.1679	-0.416**	-0.785***	-0.3099
	(0.0155)	(0.0091)	(0.02)	(0.4869)	(0.4997)	(0.7335)	(0.2152)	(0.3299)	(0.5068)
PAT				7.3521***			3.9022***		
				(0.742)			(0.3746)		
RD					8.3973***			8.7723***	
					(2.0658)			(2.1304)	
EMP48						3.8608***			2.0908***
						(0.7861)			(0.3978)
CO2	0.398***	-0.2103*	1.2093***	-3.3157***	2.9524***	-0.0889	-1.7259***	4.4352***	-0.2875
	(0.1682)	(0.1368)	(0.2356)	(0.4466)	(0.7252)	(1.3154)	(0.3359)	(0.8797)	(1.0062)
EMP48_GINIl						-0.0934***			
						(0.0184)			
EMP48_TOP5l									-0.1031***
									(0.0149)
FDI	0.0021***	-0.0011*	-0.0022**	-0.0175***	-0.0002	-0.0038	-0.0126***	-0.0006	-0.0016
	(0.0004)	(0.0007)	(0.0011)	(0.0036)	(0.0095)	(0.0052)	(0.0041)	(0.0126)	(0.0095)
GDP	0.0082***	0.0125***	0.0326***	-0.0626***	-0.0811***	-0.0439**	-0.0529***	-0.104***	-0.0399*
	(0.0026)	(0.0045)	(0.0059)	(0.0142)	(0.0193)	(0.0243)	(0.0087)	(0.022)	(0.0276)
GF_GINIl				0.0239***	0.0107	0.0011			
				(0.0089)	(0.0099)	(0.0136)			
GF_TOP5l							0.0157***	0.0309***	0.0092
							(0.0062)	(0.0119)	(0.0167)
GINIl				0.8673***	0.8647***	1.0576***			
				(0.0693)	(0.0752)	(0.1628)			
GOV	0.1125***	0.0507***	0.0077	-0.1173**	-0.2702***	-0.5238***	-0.2517***	-0.1949**	-0.4852***
	(0.0209)	(0.0133)	(0.0222)	(0.0505)	(0.1135)	(0.1148)	(0.0555)	(0.1069)	(0.1007)
INFL	0.0293***	0.0031	-0.0677**	0.0622***	0.0739*	0.1168	0.0465**	-0.0523	0.0362
	(0.0116)	(0.0046)	(0.0318)	(0.019)	(0.0524)	(0.103)	(0.0226)	(0.0511)	(0.0873)
MCAP	-0.146***	0.0397	-0.3175***	-0.127	0.184	-0.5012*	0.215***	0.2079	0.2787
	(0.0441)	(0.0311)	(0.1167)	(0.1048)	(0.2205)	(0.3473)	(0.0829)	(0.2331)	(0.3868)
PAT_GINIl				-0.1183***					
				(0.0127)					
PAT_TOP5l							-0.1089***		
							(0.0111)		
PRIV	-0.0007	-0.0005	0.0044***	-0.0314***	-0.0224***	0.0052	-0.0311***	-0.0299***	-0.0003
	(0.0019)	(0.0013)	(0.0018)	(0.0056)	(0.0049)	(0.0054)	(0.0045)	(0.0058)	(0.0061)
RD_GINIl					-0.1661***				
					(0.0428)				
RD_TOP5l								-0.2986***	
								(0.0743)	
SEC	0.0222***	0.0018	0.0155***	0.0388***	0.0622***	0.1146***	0.0518***	0.0127	0.086***
	(0.0051)	(0.0038)	(0.006)	(0.0097)	(0.0157)	(0.03)	(0.0081)	(0.014)	(0.0313)
TOP5l							0.9339***	0.8355***	1.1905***
							(0.0577)	(0.0968)	(0.1209)
TRD	-0.0092***	0.007***	0.0182***	-0.0062*	-0.0116**	-0.0432***	-0.0134***	-0.0204***	-0.0168**
	(0.0019)	(0.0022)	(0.0031)	(0.0048)	(0.0065)	(0.0112)	(0.005)	(0.0064)	(0.009)
UNMP	0.1014***	-0.0074	0.0824***	-0.2652***	0.0836**	0.1261**	-0.1358***	0.0985**	0.0154
	(0.0188)	(0.0088)	(0.0201)	(0.0448)	(0.0502)	(0.0705)	(0.031)	(0.0478)	(0.0826)
J p-val	1	1	1	1	1	1	1	1	1
J statistic	0.0755	0.1049	0.0902	0.1091	0.1463	0.0902	0.1091	0.1463	0.0902
R^2 adj	0.805	0.6086	0.8434	0.9622	0.9898	0.9724	0.9403	0.9544	0.9464
average INEQ lagged				52.5027	50.7024	48.6421	30.4357	28.7235	26.8187
direct average effect				-0.1228	0.0074	-0.1142	0.0608	0.1035	-0.0634
indirect average effect				0.001	-0.0004	-0.0281	0.0005	0.0039	-0.0277
n diff	706	335	499	706	335	499	706	335	499
n level	706	335	499	706	335	499	706	335	499
n mom	340	143	493	1172	506	1139	1172	506	1139
n total	1412	670	998	1412	670	998	1412	670	998
n unique	77	49	45	77	49	45	77	49	45
total average effect				-0.1219	0.007	-0.1423	0.0613	0.1073	-0.091

Table 28: This table presents the regression results for capital formation (CF) on green finance (GI) in the first column and investment emissions (IE) on capital formation (CF) in the second column.

outcome	CF	IE
GI	0.6786**	
	(0.067)	
CF		0.018**
		(0.0006)
GOV	0.8485**	0.0108**
	(0.071)	(0.0015)
INFL	0.0006	0.0181**
	(0.0056)	(0.0011)
TRD	0.1534**	0.0071**
	(0.0113)	(0.0004)
GDP	-0.1465**	0.003**
	(0.0177)	(0.001)
PRIV	0.0636**	0.0074**
	(0.0092)	(0.0007)
CO2	-4.6219**	0.4131**
	(0.5812)	(0.0276)
time-specific effects	yes	yes
J statistic	0.0788	0.0364
J p-val	1	1
R^2 adj	0.6015	0.437
n mom	510	152
n total	2183	4323
n unique	117	149

$^{*}p < 0.1$, $^{**}p < 0.05$

Table-specific notes: Since the outcome variable is not inequality we adjust the set of control variables. We exclude $MCAP$ and SEC, which are highly inequality specific. In the first regression (capital formation on green finance in column 1) we assume GI and GOV to be predetermined and GDP to be endogenous. In the second regression (investment emissions on capital formation) we assume $CO2$ to be endogenous.

Table 29: This table gives the moderated mediation regression results for the channel (M) via investment emissions (IE).

equation	(3)		(4)			
			GINI		TOP_5	
mediator M	IE	CI	IE	CI	IE	CI
GI	0.0841**	0.0255**	-1.3111**	0.8083**	-0.2838*	0.4228**
	(0.0122)	(0.0048)	(0.2401)	(0.1984)	(0.2015)	(0.1312)
M			10.0952**	9.4037**	5.4014**	9.4548**
			(0.588)	(0.5662)	(0.3137)	(0.3868)
INEQ lagged			0.845**	0.8017**	0.7403**	0.6853**
			(0.0165)	(0.0204)	(0.0182)	(0.0347)
GI x INEQ lagged			0.0223**	-0.0163**	0.0128**	-0.0113**
			(0.0042)	(0.0038)	(0.0058)	(0.004)
M x INEQ lagged			-0.1484**	-0.0533**	-0.104**	-0.06**
			(0.0099)	(0.0079)	(0.0082)	(0.0101)
time-specific effects	yes	yes	yes	yes	yes	yes
J statistic	0.069	0.0713	0.1104	0.1162	0.1104	0.1162
J p-val	1	1	1	1	1	1
n mom	304	270	1048	930	1048	930
R^2 adj	0.6788	0.9441	0.9762	0.9926	0.9521	0.9754
n total	1591	1476	1558	1446	1558	1446
n unique	86	84	86	84	86	84
average INEQ lagged			54.3621	54.2789	31.7725	31.7155
direct average effect (×100)			-0.0969	-0.0744	0.1228	0.0639
indirect average effect (×100)			0.0017	0.1655	0.0017	0.1918
total average effect (×100)			-0.0952	0.091	0.1245	0.2557

$^{*}p < 0.1$, $^{**}p < 0.05$

General notes: see Appendix C.
Table-specific notes: equation (3) assumes per capita carbon emissions to be endogenous and green finance to be predetermined. This means that an unexpected shock to either the average carbon emissions of the top 5% of emitters today or the investment emissions today potentially also affects the per capita carbon emission level today. In equation (4) we use the standard assumption that all terms including inequality lagged are endogenous.