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Creative Destruction During Crises

An Opportunity for a Cleaner Energy Mix

Pragyan Deb, Davide Furceri, Jonathan D. Ostry, and Nour Tawk

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ABSTRACT: Lockdowns resulting from the COVID-19 pandemic have reduced overall energy demand but electricity generation from renewable sources has been resilient. While this partly reflects the trend increase in renewables, the empirical analysis presented in this paper highlights that recessions result in a permanent, albeit small, increase in energy efficiency and in the share of renewables in total electricity. These effects are stronger in the case of advanced economies and when complemented with environment and energy policies—both market-based measures such as taxes on pollutants, trading schemes and feed-in-tariffs, as well as non-market measures such as emission and fuel standards and R&D investment and subsidies—to incentivize and hasten the transition towards renewable sources of energy.

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WORKING PAPERS

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Contents

FIGURES

TABLES

I. Introduction

Lockdowns resulting from the COVID-19 pandemic have drastically altered energy consumption patterns. Lockdowns implemented within a few months of the pandemic meant that global energy demand, especially for coal, oil, and gas, declined steeply (McGrath, 2020). According to the International Energy Agency (IEA, 2020a), energy demand dropped by 25 percent on average per week in nations with a full lockdown, and 18 percent in those in partial lockdown. This decline has been mostly driven by the reduced demand for electricity in the commercial and industrial sectors, while domestic demand for private consumption has risen by 40 percent, as millions of citizens were confined to their residences (Broom, 2020).

In contrast to the pattern for overall energy demand, generation from renewable sources has been resilient to the COVID-19 crisis. Global use of renewable energy in all sectors actually increased by 1.5 percent and, as a result, the share of renewables in electricity demand increased in many regions (International Energy Agency 2020b), including parts of Europe and the United States (Figure 1). While this reflects in part the trend increase in renewables (Figure 2), with new wind and solar projects already in the pipeline coming online in 2020, it may also reflect the "creative disruption" associated with the crisis, and the increased opportunity to improve energy efficiency and production from renewable sources of energy.

The aim of this paper is to explore this possibility and test the hypothesis that crises provide a window of opportunity for greener energy. For this purpose, we investigate the response of the share of renewable energy (and dirty energy) in total energy to major historical recessions (including financial crises and pandemics) for a panel of 176 countries over the period 1965 to 2019. Our results show that recessions—while leading to a permanent decline in energy demand stemming from lower GDP and a decline in energy intensity (that is, energy per output)—are associated with a medium-term increase (decline) in the share of renewable (dirty) energy of about 2 percentage points (see Figure 3).

These effects, however, mask important heterogeneities across countries, depending on the role of policy in facilitating a transition to greener energy. We find that supportive policy in the form of more stringent environmental protection regulation—such as emission and fuel standards, taxes on pollutants, trading schemes for carbon, and R&D subsidies and public investment in renewables—can amplify the effect of recessions to produce a near doubling (about 4 percentage points) in the share of renewables in total energy. This highlights the need for policy to support the underlying dynamics typically seen during recessions in favor of a greener energy mix.

Our paper contributes to the literature on the relationship between energy consumption and economic growth (Jakovac, 2018) which, while documenting the cointegration between these variables, has not reached a consensus on the direction of causality (see Sharma 2010, Al-Iriani 2006, Lee 2006, Soytas and Sari 2003, Stern 2000). Here, we take a systematic look at this historical relationship through the lens of growth slowdown episodes and recoveries, akin to the literature linking crises and emissions (Jalles, 2019). We attempt to disentangle the temporary effects on energy use from the more permanent shifts that represent a pattern of recoveries from recessions by focusing on deviations from established trends. Our paper undertakes the first analysis in the literature of the impact of growth slowdowns on the evolution of the energy mix.

The remainder of the paper is structured as follows. Section II provides a brief overview of the literature on obsolescence and creative destruction and provides intuition on how these trends interact with growth slowdowns and the use of renewables. Section III describes our data and empirical framework. Section IV presents our results while Section V checks for robustness. Section VI extents the analysis to assess the impact by type of economy and the role of supportive policy in the form of environmental protection stringency. The last section concludes.

II. Recessions, obsolescence, and policies

Recessions are associated with a sharp decline in energy demand and the COVID-19 pandemic is no exception (see Buechler et. al. 2020). Lower demand in turn leads to excess electricity supply; and since the storage options for electricity are limited, power plants tend to be shut down. This is specially the case for dirty coal-based plants, because of their older technology and higher marginal cost of operation (including fuel costs).

Whether this crisis will provide investors an incentive to continue investing in old coal-based plants or rather in more efficient, greener plants remains an open question. On one hand, the disruption in financing brought by the crisis may reduce innovation in new energy through lower research and development, which is highly procyclical. On the other hand, the recession may give firms a stronger incentive to improve their efficiency leading to "creative destruction".

The idea that units that embody the newest processes and product innovations are continuously being created and outdated units destroyed goes back to Joseph A. Schumpeter (1939, 1942).[1] Industries undergoing continuous creative destruction can accommodate variations in demand in two ways: they can vary either the rate at which production units that embody new techniques are created or the rate at which outdated units are destroyed. The economic disruptions brought about by recessions act as a time of cleansing (see Caballero and Hammour, 1994), with faster obsolescence of outdated units amid lower demand and prices. In addition, the lack of demand created by the recession results in lower marginal cost of reallocation of both labor and capital (see e.g., Davis and Haltiwanger, 1990; Aghion and Saint- Paul, 1998; Gali and Hammour, 1991; Hall, 1991).

A stark historical example of this effect has been documented by Bresnahan and Raff (1991, 1993) in their study of the effect of the Great Depression on the motor vehicles industry. Using census panel data for the United States, they find that the large contraction in automotive production during the depression resulted in a permanent structural change. At the start of the great depression, the diffusion of mass production techniques in manufacturing was small, with a substantial segment still based on skilled craftsmanship. But the plant shutdowns that occurred during the great depression due to lack of demand were concentrated in smaller, less productive craftsmanship plants, while plants that had adopted the mass-production system maintained a competitive advantage that allowed them to survive. The result was a shakeout or "cleansing" of the productive structure, as most plant shutdowns were permanent and the automotive industry that emerged afterwards was much more reliant on mass-production and automation—a process that likely would have taken much longer absent the destruction caused by the great depression. In addition, they note that even during the massive

[1] There exists a rich body of research analyzing the role of creative destruction in models of economic growth that embody technological progress (see, e.g., Johansen, 1959; Solow, 1960; Phelps ,1963; Sheshinski, 1967; Aghion and Howitt, 1992; Grossman and Helpman, 1991; Aghion, Akcigit, and Howitt, 2015).

destruction process of plant shutdowns, a sizable number of new mass-production plants entered the industry. Similar evidence can be found during the Great Recession (see Pardo, 2016; Rembert, 2018).

Turning to the green energy sector, Peters et al. (2012) find that when crises were triggered by energy shocks such as the 1970s and 1980s oil crises, they contributed to major improvements in the production of renewable sources of energy and energy efficiency. While this finding in itself is not surprising, as the increase in the cost of fossil fuels would naturally boost energy efficiency and substitution toward renewables, they also argue that in times of crisis, countries tend to sustain economic output by supporting less energy intensive activities. The Global Financial Crisis also has been associated with a significant increase in renewables (see UNEP, 2009; IEA, 2020c). For example, Jaeger (2020) finds that "U.S. solar electricity generation increased over 30 times from 2008 to 2015, and wind generation has increased over three times." According to researchers at the World Resource Institute, "the United States, China, and Germany became renewable energy leaders in part because of programs coming out of the Great Recession."

Policy can be a powerful tool in boosting these underlying trends and assisting the transformation towards renewables (OECD, 2010). For example, the Climate Change Levy (CCL) introduced in the United Kingdom in 2001 had a strong negative impact on energy intensity and electricity use (see also Martin, de Preux and Wagner, 2011; Martin and Wagner, 2009). Similarly, in Spain, support for R&D and technological innovation led to higher investments in environmental protection, including in the use of renewable energy sources. Introduction of standards and charges for Sulphur oxides in Japan during the 1960s and 1970s resulted in reductions in the level of these pollutants and significant technological innovation.

Bowen and Stern (2010) further argue that downturns provide a "very good opportunity to undertake a necessary step change in the public spending component of environmental policies and to start working through a backlog of public investment to improve the environment." Drawing lessons from the Global Financial Crisis, Agarwal et. al. (2020) provides evidence that the implementation of timely and properly designed green stimulus measures can generate economic growth, create jobs and bring about environmental benefits, but they note the trade-offs between competing economic, environmental and social policy objectives, underscoring the importance of proper policy design.

III. Data and empirical framework

The data on energy comes from the energy dataset maintained by Our World in Data which is sourced from the BP Statistical Review of World Energy, with additional energy consumption data from the SHIFT data portal and electricity consumption and mix data supplemented from the EMBER global electricity dashboard. As a first step, we use the data on overall primary energy—a measure of energy as found in nature, for example blocks of coal, crude oil, natural gas, biofuels, nuclear, hydro, geothermal, solar or wind—and its subcomponents such as oil and coal which is available for 176 countries from 1965 to 2019. In addition, we use data on overall electricity and energy mix—electricity from fossil fuels, nuclear and renewable sources—which is available for a slightly smaller set of 172 countries over the period 1985–2019 and is the key focus of the paper.[2]

[2] As an additional check, we also use data from the International Energy Agency's World Energy Balances database to check the robustness of our results. This dataset has coverage for around 130 countries over the period 1980 to 2016. All our main results continue to hold.

The paper analyses the impact of recessions—defined as periods of negative real GDP growth—on the overall energy use and mix. While we use recessions as our baseline specification, we also check for robustness of our results using various other economic shocks. First, we look at the impact of financial crises, data for which are available from Laeven and Valencia, 2020. Second, we explore the impact of pandemics. Following Furceri et al. (2020), we identify five major pandemic events—SARS in 2003; H1N1 in 2009; MERS in 2012; Ebola in 2014; and Zika in 2016. To capture the severity of the pandemic episodes, we look at the number of infections per capita. Third, instead of focusing just on periods of negative growth, we identify peaks and troughs in economic activity using the Harding-Pagan algorithm applied to both annual real GDP and annual per-capita GDP. We then identify peak to troughs as periods of growth slowdowns. Finally, we test our results using changes in (log) GDP as opposed to recessionary events.

The various economic data needed for our analysis are taken from the International Monetary Fund's World Economic Outlook database, the World Bank's World Development Indicators and the Penn World tables. Environmental policy variables are taken from the Environmental Policy Stringency Index dataset of the OECD (Botta and Kozluk, 2014). These data are the most comprehensive available source for policy measures across countries (28 OECD and six BRICS countries) and time (1990–2015). The dataset helpfully provides a breakdown by instrument type. The EPS data allows us to test the effect of different instruments—scaled from 0 (not stringent at all) to 6 (very stringent) —relative to an overall aggregate index consisting of both market-based and non-market-based measures. Here, market-based measures include instruments such as taxation on emissions, trading schemes and feed-in tariffs, while non-market-based indicators capture legislation on emission limits and R&D subsidies, among others.

To estimate the dynamic effects of recessions on energy use and mix, we use the local projection methods proposed by Jordà (2005) and estimate impulse response functions directly from local projections. Specifically, we estimate:

$$e_{i,t+h} = u_i + \theta_h s_{i,t} + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta e_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} \gamma_{h,\ell} \Delta s_{i,t-\ell} + \varepsilon_{i,t+h} \quad (1)$$

where $e_{i,t+h}$ is the energy variable, in country i at date t. This energy variable either enters the equation as the logarithm of the energy use (in terawatt-hour) or the share of different sources in total electricity in the case of the energy mix variables. $s_{i,t}$ denotes the measure of growth slowdown, u_i are country-fixed effects to account for time-invariant country-specific characteristics. We do not explicitly include time dummies in our baseline specification because many growth slowdown episodes and crises—such as pandemics and financial crises—are global in nature and time fixed effects would absorb their impact, which we want to explicitly capture. In addition, when exploring the role of environmental policy regulation (see below) we observe that many of the policy initiatives were synchronized globally, either on account of them being an outcome (direct or indirect) of multilateral climate agreements or part of a regional package (in particular for the countries in the European Union). However, to allow for better identification, and as a robustness check, we include both time dummies and a country-specific time $trend_i$ to capture trends in energy use or the share of renewables, as well as fluctuations in global fuel prices. Our main results continue to hold.

Equation 1 is estimated for an unbalanced panel of up to 176 countries over the period 1965–2019, for each year *h*=0,1, 2... The impulse response functions computed using the estimated coefficient θ_h, with the associated confidence bands obtained using robust standard errors clustered at the country level. The baseline assumes 2-lags, but the results are robust to different specifications of lags and leads. In the case of energy use, the coefficients can be interpreted as the change in consumption *h* years after the shock relative to a baseline of no growth slowdown, while in the case of energy mix, the interpretation is that of a change in the share of say, solar power, in total electricity, *h* years after the growth slowdown episode. We also estimate equation 1 for subsamples by income group, i.e., advanced economies and emerging market and developing economies.

We use the smooth transition autoregressive model developed by Granger and Terävistra (1993) to test whether the effect of recessions on the share of renewables varies across different levels and types of environmental protection "regimes". This method allows the effect of recessions to vary smoothly across regimes by considering a continuum of states, thus making the functions more stable and precise. Specifically, we estimate:

$$e_{i,t+h} = \mu_i + \theta_h^L F(z_{i,t}) * s_{i,t} + \theta_h^H (1 - F(z_{i,t})) * s_{i,t} + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta e_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} \sigma_{h,\ell} \Delta s_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} \partial_{h,\ell} EPS_{i,t-\ell} + \varepsilon_{i,t+h}$$

with $F(z_{it}) = exp^{-z_{it}}/(1 + exp^{-z_{it}}),$ (2)

where *z* is the environmental protection stringency or its subcomponent, normalized to have zero mean and a unit variance and $EPS_{i,t-\ell}$ is the corresponding lagged value of the measure. The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. The coefficients θ_h^L and θ_h^H capture the impact of recessions in cases of very low EPS ($F(z_{it}) \approx 1$ when z goes to minus infinity) and very high EPS ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively.

IV. Results

Before moving to the core results on the effects of recessions on energy mix, we present the results on the effect of recessions on energy use. As expected, and in line with previous research, we find that recessions are associated with a significant and permanent decline in energy use. Figure 4 summarizes our main results on energy use. While energy use expectedly declines following recessions, even after five years, primary energy use is around 10 percent below their pre-recession trend. A similar pattern can be seen in specific sectors—coal and oil demand after a recession is down by around 5 and 8 percent respectively after five years, while electricity demand declines by around 7 percent. Although there is a permanent level effect, the slowdown in growth of energy use is temporary, with growth rates returning to trend after around three years (see Annex Figure 1). In addition to the effect on energy use, there is also a statistically significant shift in energy intensity—defined as energy used per unit of output, measured by the level of GDP. Results highlighted in Figure 5 show that energy intensity declines durably after a recession. The initial decline in energy use is in line with the decline in output, resulting in no statistically significant change in energy intensity, but over time, as output recovers, energy intensity declines (see Annex Figure 2).

Having established the negative impact of recessions on energy use and intensity, we turn our attention to the question on energy mix and try to answer the following question: does the share of renewable energy durably increase after a recession? Our main results, shown in Figure 6, confirm that after a major recession, the energy mix becomes greener, with the share of electricity generated from coal going down by about a percent after five years, while the share of renewables increases by almost 2 percent. Annex Figure 3 shows the impulse response of the level of electricity generated by renewables (as opposed to share of total electricity) and confirms that electricity production from renewables is resilient to recessions, despite the overall decline in energy demand as seen in Figure 4, resulting in an increase in share of renewables. Moreover, while overall energy intensity declines, the intensity of renewables—renewable energy as a share of GDP—increases durably after recessions (Annex Figure 4).

This reflects the fact that once built, renewables like hydro, wind and solar have a very low marginal costs of operation and are generally used before other sources of electricity—renewables receive priority in the grid and are not asked to adjust their output to match demand insulating them from the impacts of lower electricity demand. As a result, during recessions, when demand for energy is low and overall capacity utilization falls (Annex Figure 5, top chart), older power plans, primarily coal-based plants, are the first to be shut down given their high marginal cost of operation (fuel costs) and the relative inefficiency of the older technologies. Once demand recovers, investors choose not to put in the funds to restart these environmentally unfriendly and relatively inefficient power plans and instead invest in newer and renewable technologies to address the increase in demand for electricity. This is corroborated by the large increase in investment in renewable observed during the global financial crisis (Annex Figure 5, bottom panel). Within renewables, both solar and hydro get a boost, with the results for wind energy less robust and virtually no change in the share of nuclear in total energy (Figure 7).

V. Robustness

We check the robustness of our results by exploring the role of different types of growth slowdown episodes. While Figure 6 was based on recessions (negative growth), in Figures 8 and 9, we look at the impact of financial crises (Laeven and Valencia, 2020), pandemics, peak to trough slowdowns identified by the Harding-Pagan algorithm applied to both annual real GDP data and annual per-capita GDP data, and simple GDP growth. Figure 8, top panel, shows results similar to those obtained for recessions, with total electricity use declining by around 6 percent after five years, with the share of renewables increasing by a little over 1 percent. Annex Figure 6 reports the impact of financial crises on other variables (primary energy, oil, electricity from coal, electricity from solar wind and hydro), and we continue to find robust and statistically significant results, with financial crises decreasing primary energy demand by around 8 percent but giving a boost to renewables like solar, wind and hydro. The relatively greater disruption in financing and investment inherent in a financial crisis likely explains the marginally weaker impact on primary energy—slower pace of innovation and investment compared with a generalized growth slowdown—but this is not picked up in the case of electricity demand.

Turing to pandemics (Figure 8 bottom panel), the impact takes longer to develop and is weaker—this can be explained by a lower initial energy demand from businesses being partially offset by higher demand from households due to lockdowns and increased work from home. Nevertheless, the impact on energy mix remains positive with an increase in the share of renewables. Results for other indicators are presented in Annex Figure 7.

The analysis thus far has relied on various economics shocks. But we also look at the impact of generalized growth slowdowns, measured as the period after growth peaks to its trough. As noted earlier, peaks and troughs are identified by the Harding-Pagan algorithm applied to both annual real GDP data and annual per-capita GDP data. Our baseline results continue to hold, with a decline in overall energy demand and an increase in the share of renewables (Figure 9 top and middle panel). However, the results for the changes in the energy mix are somewhat weaker and less statistically significant, particularly for solar and wind energy (see Annex Figures 8 and 9). A likely explanation is that, in contrast to recessions and recoveries, prolonged periods of slow growth result is longer periods of lower investment generally, including in renewables. Hydro, with its long gestation lag, is less affected. In addition, in the absence of the immediate shock from the recession (negative growth), the creative destruction channel is likely to be weaker and more drawn out as well. As a final check, we also look at the impulse responses to GDP growth and find that the share of renewable energy is counter-cyclical (Figure 9 bottom panel and Annex Figure 10).

Alternative specifications

We conduct a number of additional checks to gauge the robustness of our results. Following the literature on local projections, our baseline specification controls for lags of the shock variable—economic recessions measured by periods of negative growth in the baseline. While the baseline regressions use two lags of both the dependent variable and the recession dummy, our results are robust to alternative lags. Figure 10, top panel summarizes the results from using eight lags. To further control for pre-existing trends as well as the persistence of the recessions, we also included leads of the shock variable in the regression. Results continue to hold with two and eight leads (Figure 10 middle and bottom panel).

As an additional robustness check, we control for lagged growth in our regression directly. The impulse responses are presented in Figure 11, top panel, and Annex Figure 11 and all our results continue to hold. In addition, as noted earlier, we do not include time dummies and country-specific trends in our baseline regressions to avoid excluding global crises and pandemics from our analysis. However, all our results continue to hold if we include time dummies (Figure 11 middle panel and Annex Figure 12) and are also robust to controlling for country-specific time trends (Figure 11 bottom panel and Annex Figure 13). These results confirm that our results are robust to other global shocks—such as swings in fuel prices and technological changes that affect production costs—which are picked up by the time effects.

While reverse causality is unlikely to be an issue (as the energy mix does not affect the occurrence of a major recession), a potential concern is omitted variable bias where the omitted factors are (directedly and indirectly) correlated with major recessions and the energy mix.[3] To address this concern, we repeat the analysis to include the following set of additional controls: population growth; change in urbanization; credit growth; investment growth; changes in the share of manufacturing in total value added; export growth. The inclusion of these controls does not affect our main results (Figure 12).

While the inclusion of the additional controls helps to mitigate concerns regarding omitted variable bias, using the observables to identify the bias from the unobservable variables requires making further assumptions about the covariance properties of the two sets of data.[4] To address this issue, we use the bias-adjusted treatment

[3] Indeed, Granger causality tests (not reported but available upon request) suggest that lags of the energy mix do not contribute to explain the occurrence of major recessions.

[4] In particular, the case in which the omitted variable bias is fully identified by the observed controls corresponds to the extreme assumption that the relationship between treatment and unobservable variables can be fully recovered from the relationship between treatment and observables (Altonji, Elder, and Taber 2005; Oster 2019).

effect estimator proposed by Oster (2019).[5] The results also in this case are similar to, and not statistically different from, the baseline.

Another concern is that the results are picking up the effect of trends in energy mix rather than the effect of the crises per se. To address this, we also checked the validity of the parallel trend assumption—that is, the assumption that the energy mix in the treatment and counterfactual were following a parallel trend before the recession. We do this by running a placebo test where the impulse responses are computed by randomly assigning the date of the recession across the sample. Reassuringly, the impulse response functions obtained by attributing randomly recession dates do not point to any significant effect on the energy mix (see Figure 13). In other words, the impulse response functions obtained in the baseline (Figures 5-7) are indeed capturing the effect of the recessions and not of differences (or factors driving differences) in energy mix trends between a country experiencing a recession (treatment) and a country with no recessions (control).[6]

VI. Country characteristics and environmental policy

Do the results differ between advanced economies and emerging market and developing economies? We find that the share of renewables in total electricity rises strongly in the case of advanced economies, but the results are weaker and quantitatively smaller in the case of emerging market and developing economies (Figure 14). This in part reflects the fact that our sample starts from 1985, when the prospects for renewable energy other than hydro was less certain and the technology needed for generating solar and wind energy was largely restricted to advanced economies. In addition, it is likely driven by that fact that most emerging market and developing economies lack the resources to make the costly investments necessary for renewable sources and have lower and less stringent environmental protection regulation and enforcement that can hasten the adoption of renewable sources of energy.

On the last point, we formally test the impact of varying degrees of environmental protection on the change in energy mix after a recession.[7] However, as noted earlier, comprehensive cross-country data on environmental policy variables are only available for a limited set of relatively advanced economies and over a shorter time period. We therefore begin our analysis by confirming that our baseline results hold for this more limited sample (Figure 15). Then, as a first step, we introduce the environmental policy variables in our baseline specification. In line with the literature highlighting that role of environmental policy stringency in accelerating environmental innovation (Hassan and Rousselière, 2021), Table 1 confirms that both overall environmental protection stringency (EPS) as well as market and non-market EPS are associated with a higher share of renewables in total electricity after a recession. In addition, the impact increases over time. In particular, we find that a unitary

[5] Specifically, we used the Stata *pscalc* command assuming: (i) a value of 1 for the relative degree of selection on observed and unobserved variables (δ); and (ii) a value of 1 for Rmax—the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls.

[6] Intuitively, if the improvement in energy use and mix is driven by a trend and not any underlying dynamics associated with the shock (economic recession in the baseline), then we should find statistically significant results from assigning recession dates randomly.

[7] It is possible that a crisis triggers the adoption of more stringent environmental protection regulation, which in turn affects energy mix after the recession. We test for this and find that the effect of crisis on environmental policies is not statistically significant in our sample. Bourcet (2020) provides a survey of the literature on the determinants of renewable energy deployment, including the role of environmental policy on electricity markets (see also Cullen and Mansur, 2017).

increase in the EPS indicator (such as the United Kingdom in 2010 when various climate change policies were strengthened, including the introduction of feed-in-tariffs and inflation indexing of the CCL levy) can lead to medium-term increase of 3-5 percentage points in the share of renewable energy. This result has important implications *per se* as it suggests that climate change polices can be effective in fostering the transition to a greener economy.

Next, we use the smooth transition autoregressive model outlined in Equation 2 to formally assess the impact of EPS (high and low EPS "regimes") in affecting the energy mix after a recession. Our headline result shown Figure 16 confirms that overall environmental protection stringency (EPS) can boost the transition towards renewable energy, with high EPS associated with an increase in the share of renewables in total electricity after a recession, while the effect is not statistically significant in regimes with low level of EPS. While on average, we find that a recession is associated with a 2 percentage points increase in the share of renewables (based on the comparable restricted sample shown in Figure 15), countries with high EPS see a much larger increase—almost double at around 4 percentage point. In addition, the effect of EPS is larger during recessions.

Digging deeper, we look at both market and non-market-based EPS. Market based EPS comprise of taxes on pollutants, trading schemes such as carbon trading, energy savings certificates and green energy certificates, and feed-in-tariffs for renewables. In contrast, non-market-based EPS include emission and fuel standards and R&D incentives and investments, including public investment (see Botta and Kozluk, 2014). We find that both market and non-market EPSs are associated with an increase in share of renewables after a recession (Figure 17). These results are confirmed by looking more narrowly at specific measures (see Figure 18). Higher emission and fuel standards are associated with a larger shift towards renewables after recessions. Particularly relevant for renewable electricity generation are feed-in-tariffs and trading schemes such as green certificates and white certificates.[8]

VII. Conclusions

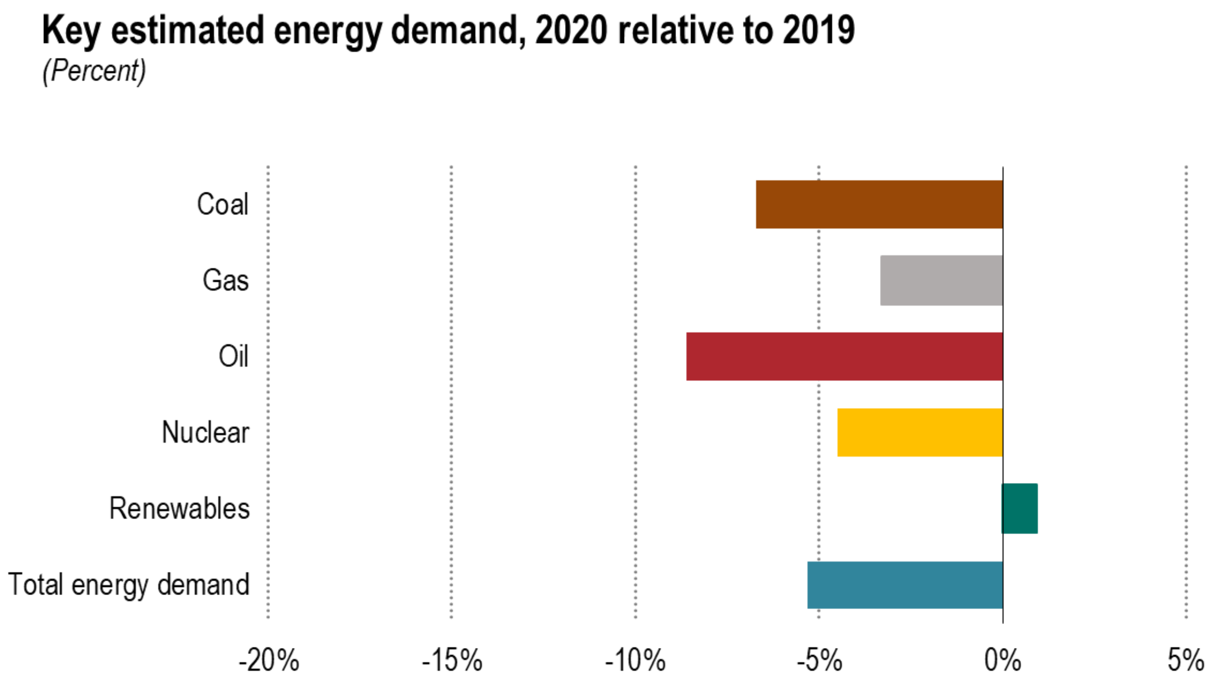
This paper explores the historical relationship between growth slowdowns and energy use to identify systematic and permanent shifts inherent in the pattern of recoveries from recessions. The empirical analysis confirms that growth slowdowns, including those engendered by pandemics and financial crises, result in a permanent increase in energy efficiency and a corresponding decline in the energy intensity of output, with a disproportionate impact on dirty energy. These effects are stronger in the case of advanced economies, and in the presence of stronger environmental policies that incentivize the shift towards renewable energy. Our results confirm that both non-market-based policies in the form of emission and fuel standards, R&D incentives and subsidies and public investments, as well as market-based measures such as trading schemes for carbon, renewable energy certificates and energy saving certificates, can be effective in boosting the transition towards renewables. As noted by the OECD, taxes and other environmental policy instruments can complement each other. And even though renewable sources of electricity are becoming cost-competitive with fossil fuels and nuclear power (Union of Concerned Scientists, 2017) and will soon no longer need subsidies, policies such as

[8] Green certificate is an obligation, which can be traded, to source a given percent of electricity from green sources. White certificates are tradeables documents confirming energy saving, with more stringent policy associated with higher overall energy savings targets.

carbon pricing and more stringent climate policy can encourage demand for renewable energy and help meet ambitious climate targets (Baldwin, Cai, and Kuralbayeva, 2020).

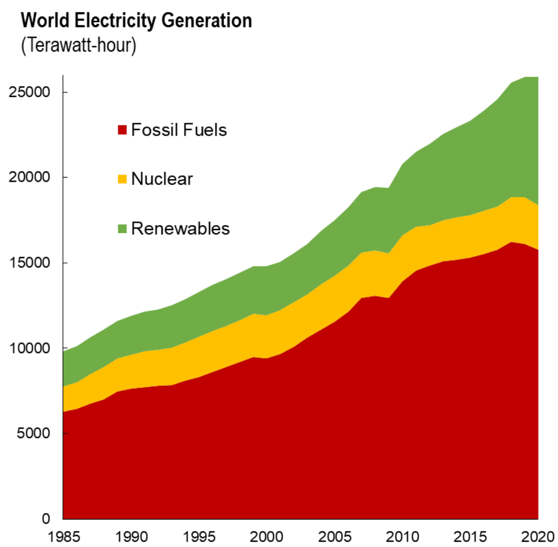
Although climate change and clean energy policies can entail political costs in the form of opposition from both energy-using industries as well as the public at large, these costs can be avoided if the design of mitigation policies takes into account political economy dimensions and if complementary policies are deployed to protect vulnerable households (see Furceri, Ganslmeier, and Ostry, 2021). Although the migration to renewables might be socially less costly during times of booms—easier for obsolete power plant workers and coal miners to find new jobs during a boom—it still requires strong and politically costly policy actions in the form of standards or taxes to close down a power plant during a boom when energy demand is high. Recessions, such as the current one, and the associated "creative destruction", provides a window opportunity to foster reforms to achieve a more resilient and greener recovery (Georgieva, 2020).

Figure 1. Energy trends during the pandemic

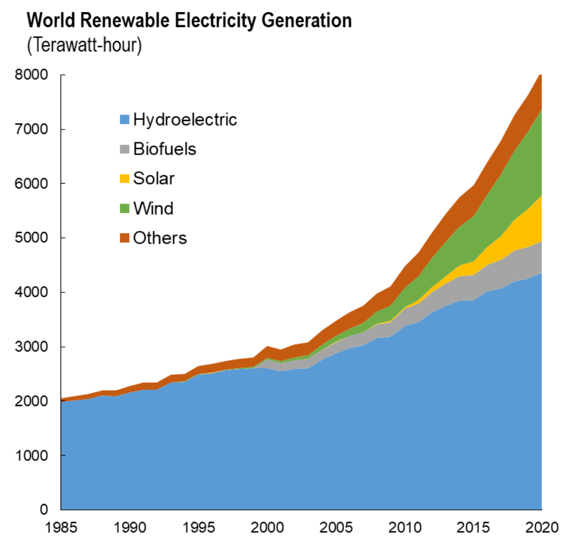


Source: International Energy Agency. World Energy Outlook 2020

Figure 2. Trend in electricity generation

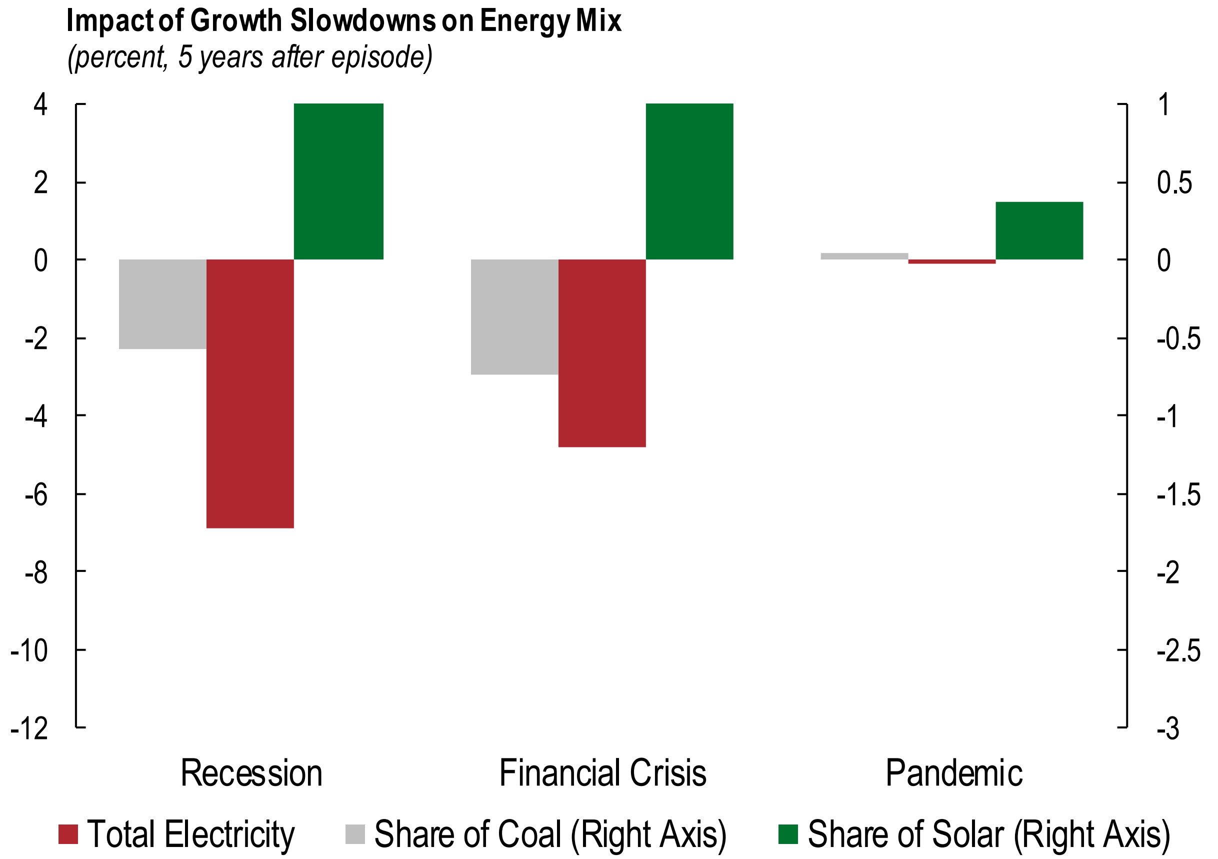


Source: Our World in Data Renewable Energy Database



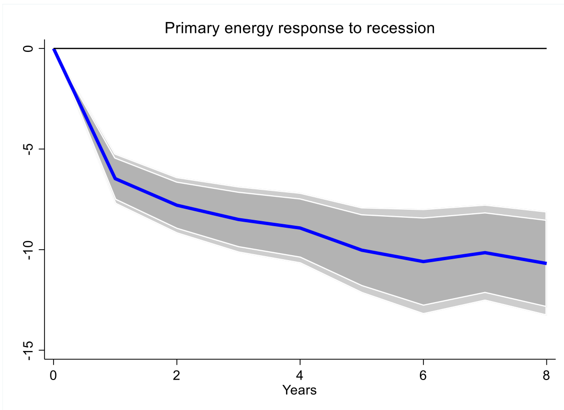
Source: Our World in Data Renewable Energy Database

Figure 3. Summary of main results

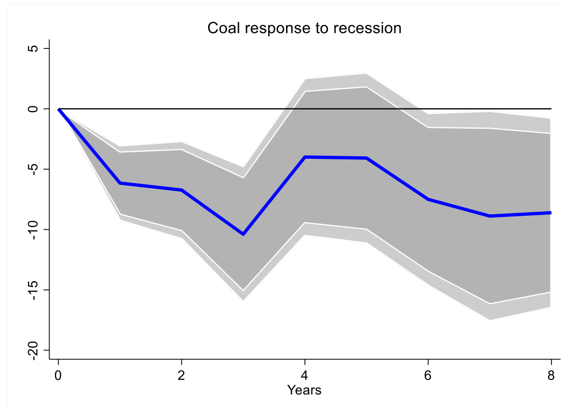


Note: Bars show the impact of growth slowdowns after five years on total electricity use and energy mix estimated using equation (1).

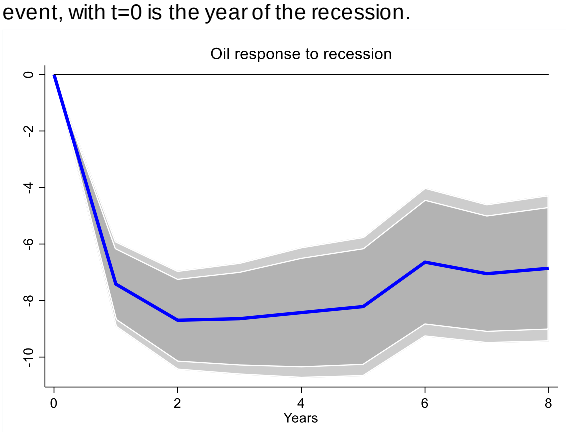
Figure 4. Impact of recessions on energy use



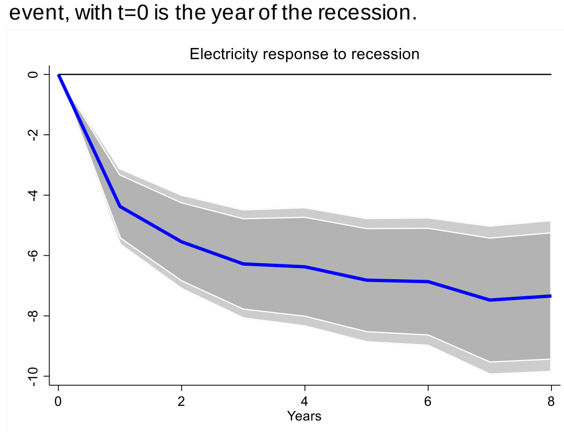
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

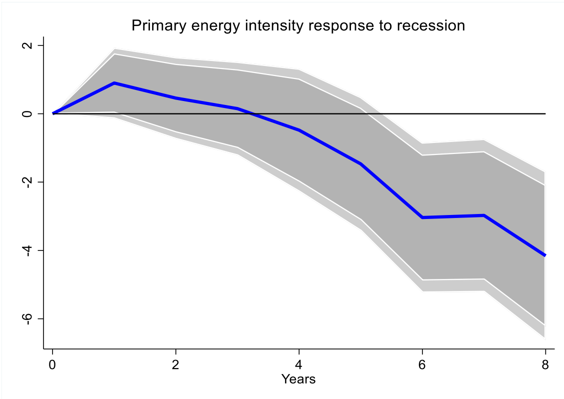


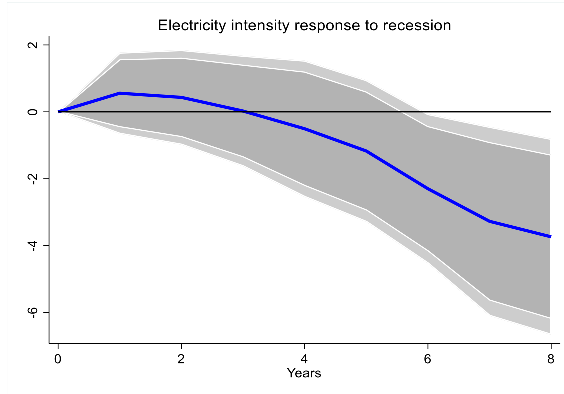
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Figure 5. Impact of recessions on energy intensity

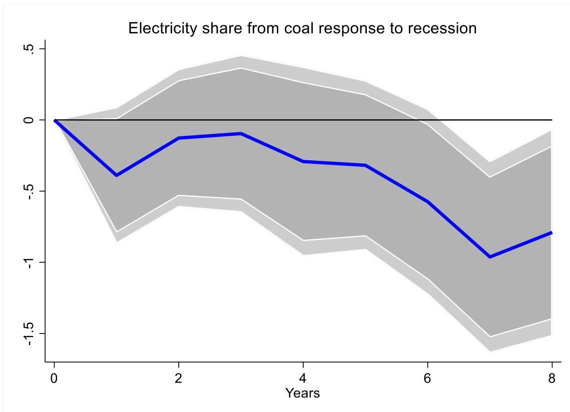




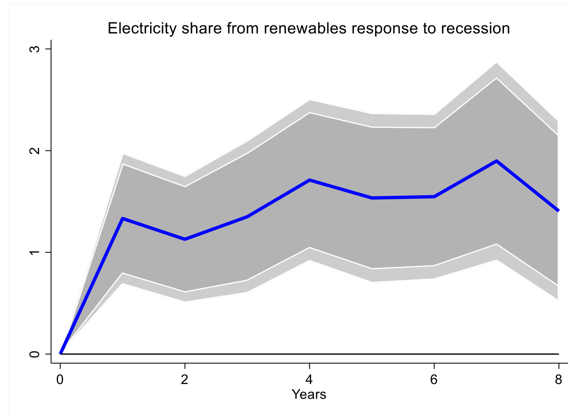
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Figure 6. Changes in energy mix after recession

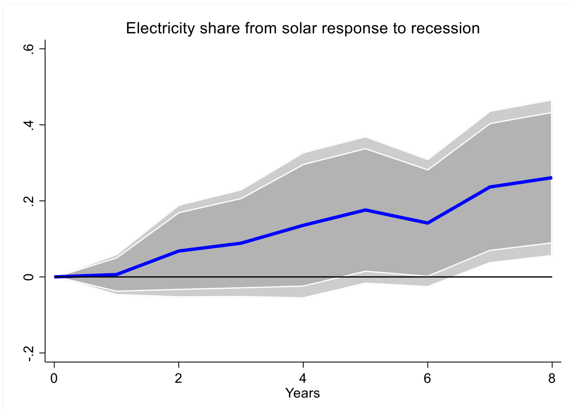


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

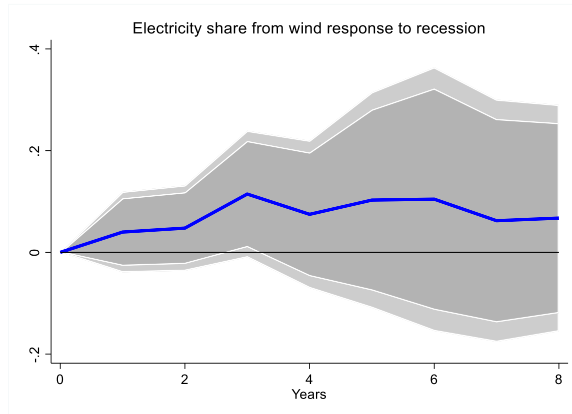


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

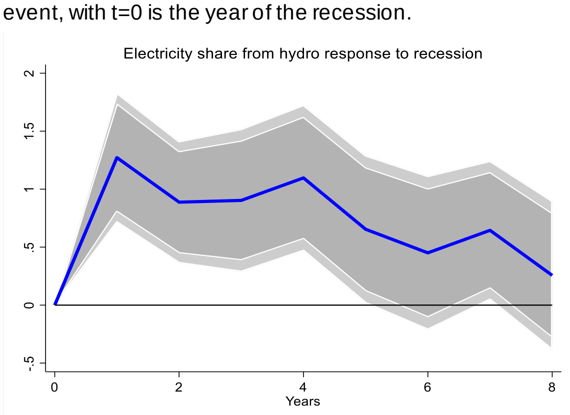
Figure 7. Impact of recession on renewables



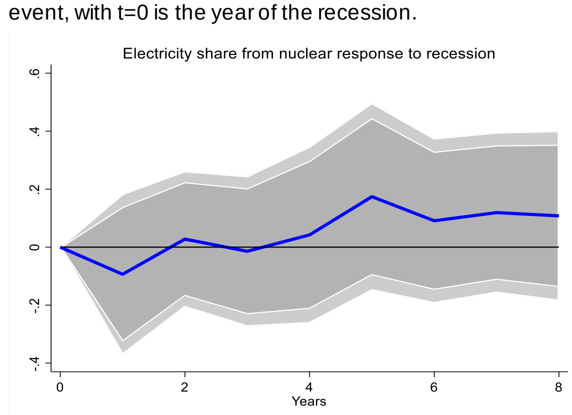
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

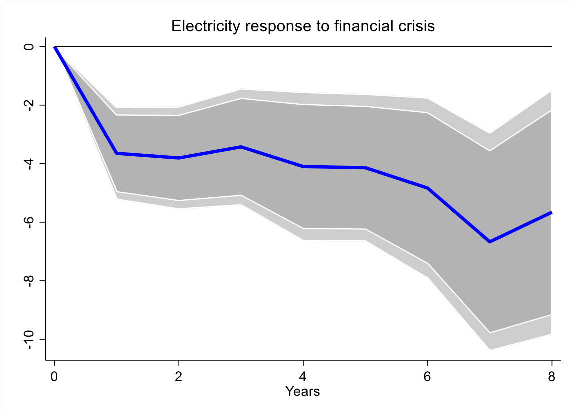


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

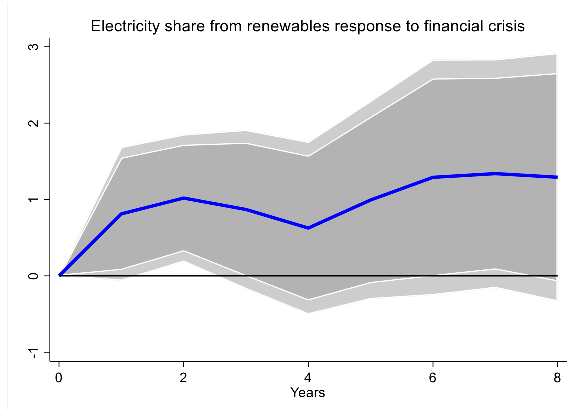


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

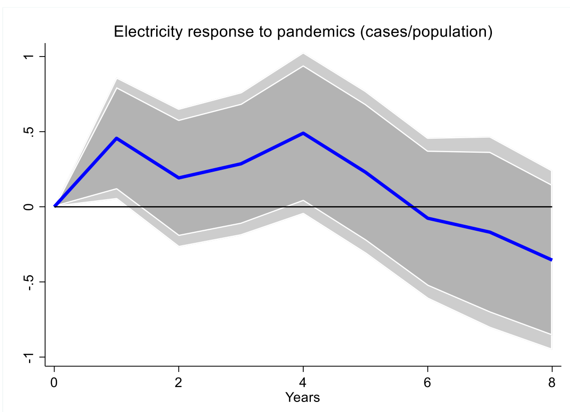
Figure 8. Robustness to different types of crisis



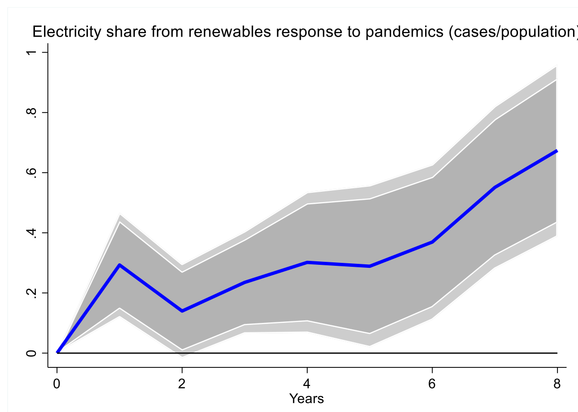
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

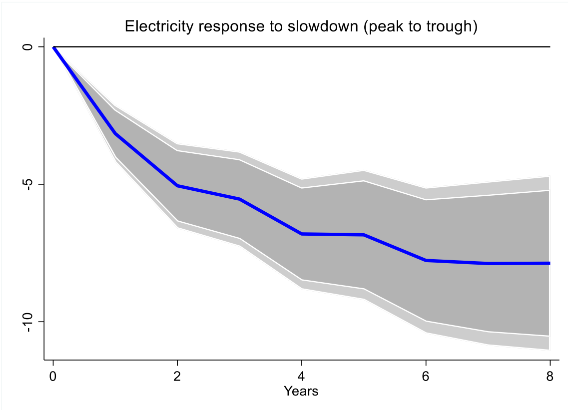


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

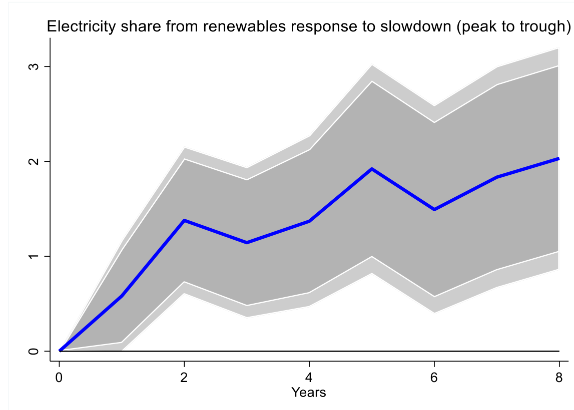


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

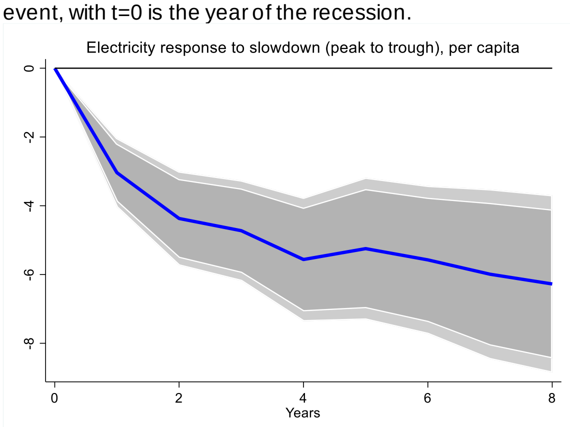
Figure 9. Robustness to other economic shocks



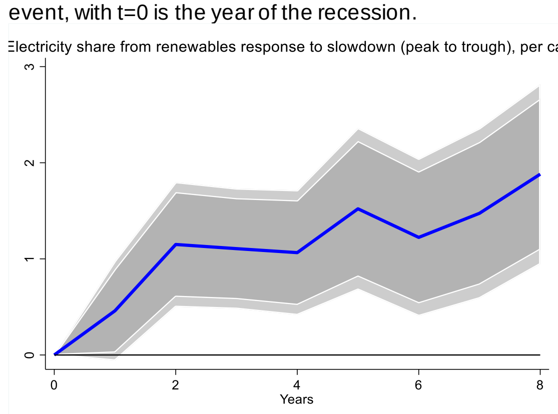
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



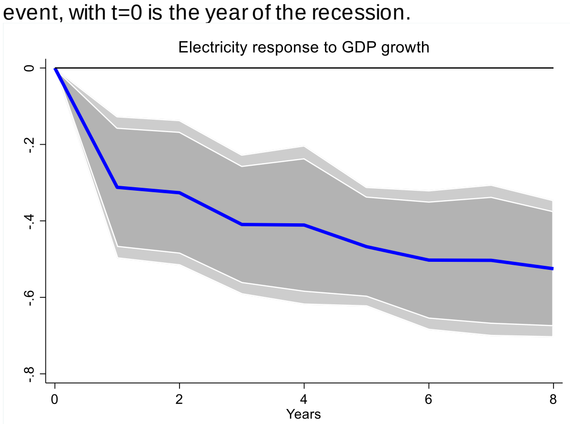
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



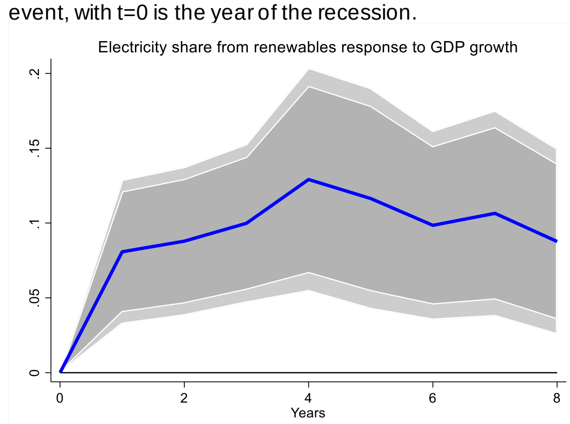
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



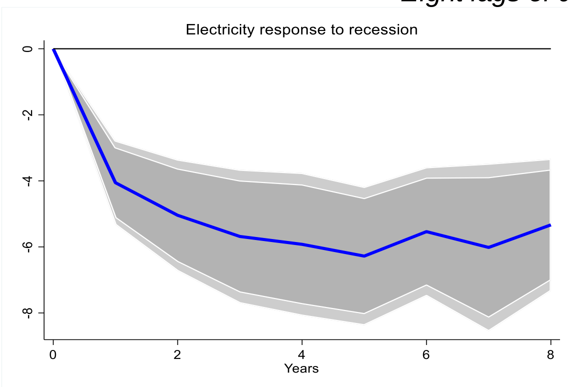
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).



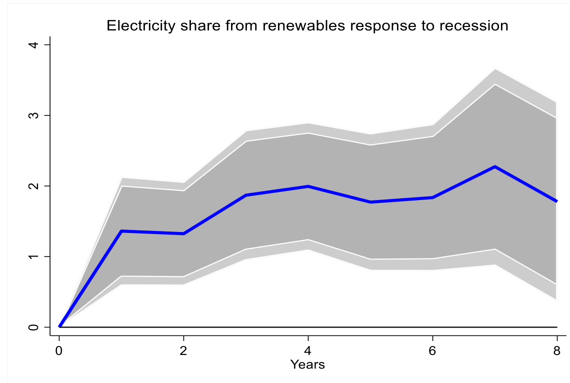
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).

Figure 10. Robustness to lags and leads

Eight lags of dependent and shock

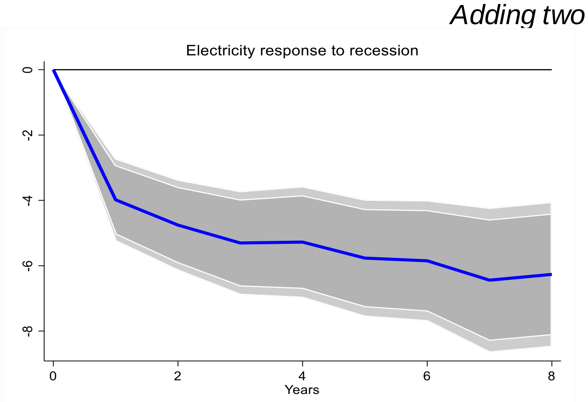


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

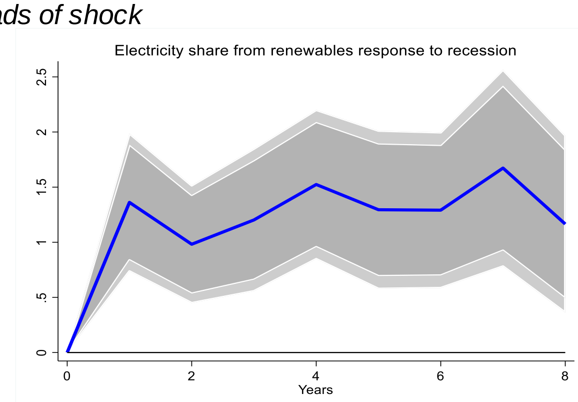


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Adding two leads of shock

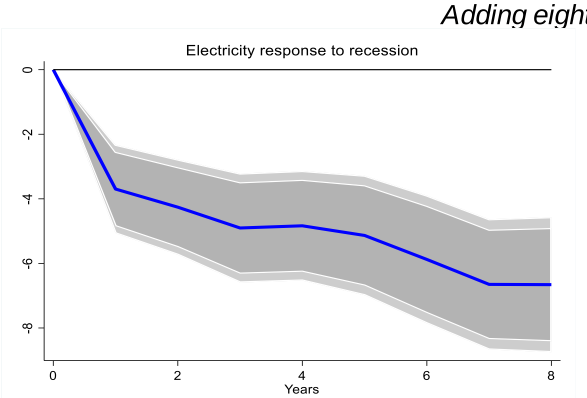


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

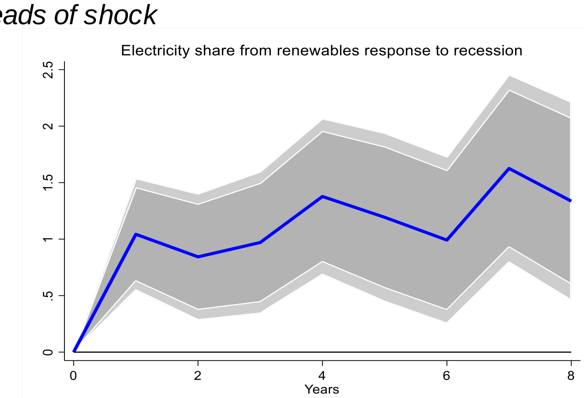


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Adding eight leads of shock



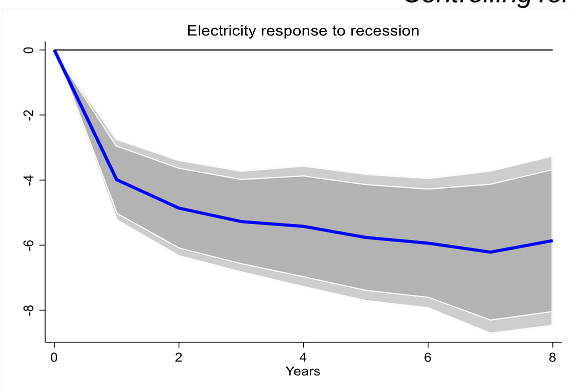
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



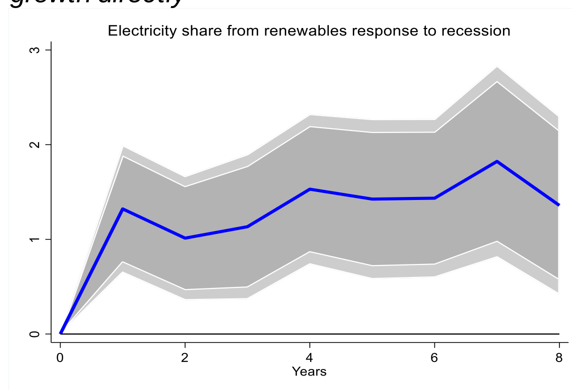
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Figure 11. Robustness to alternative specifications

Controlling for GDP growth directly

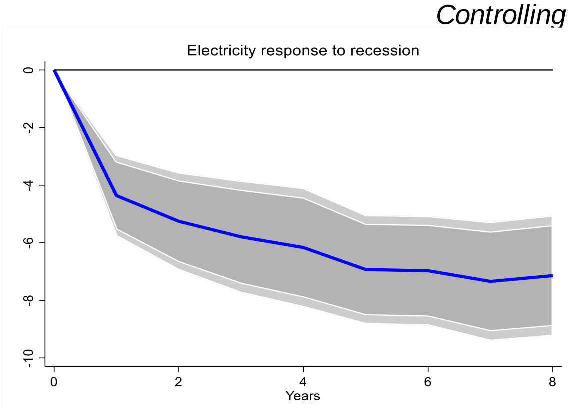


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

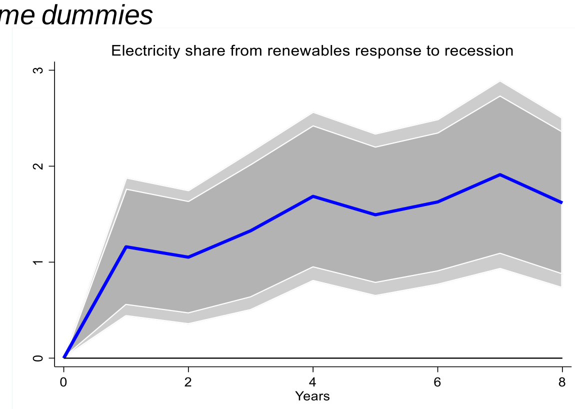


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Controlling for time dummies

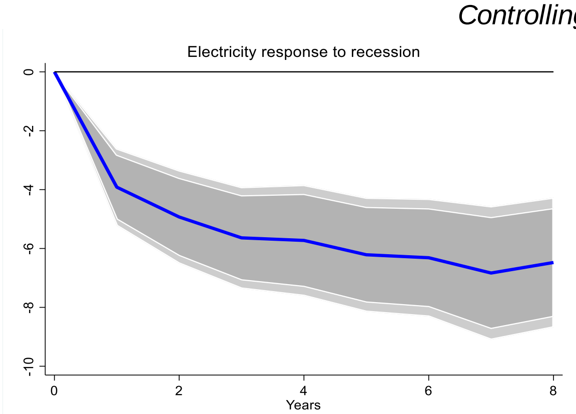


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

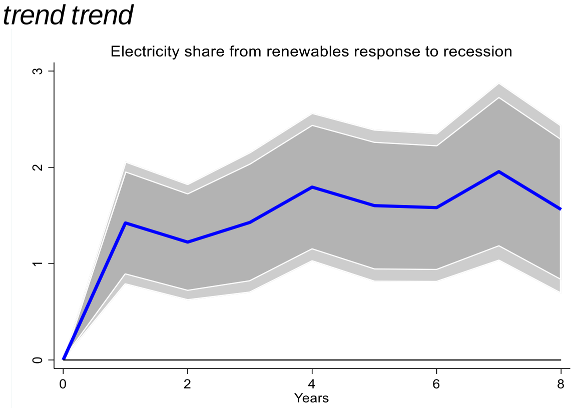


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Controlling for trend trend

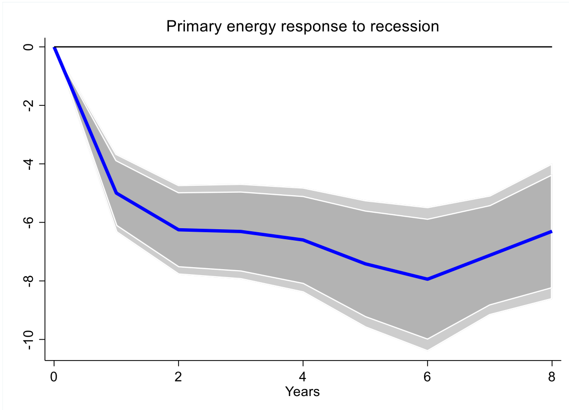


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

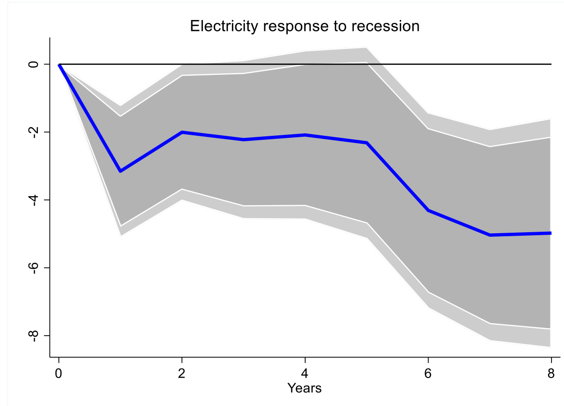


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

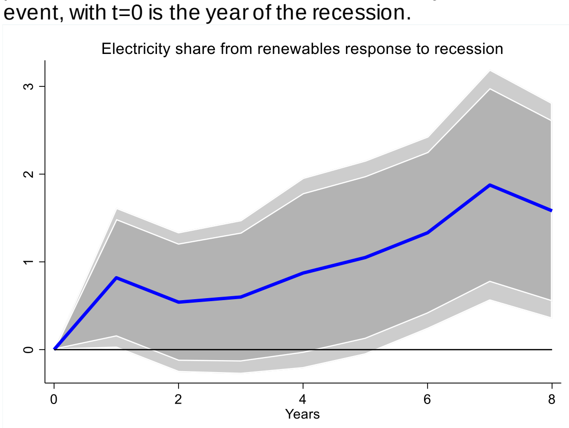
Figure 12. Robustness – Additional controls



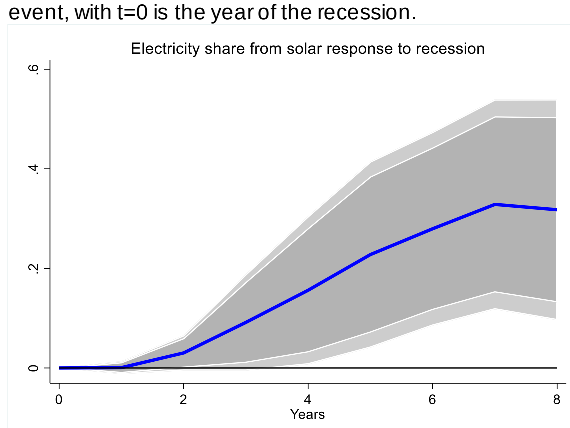
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



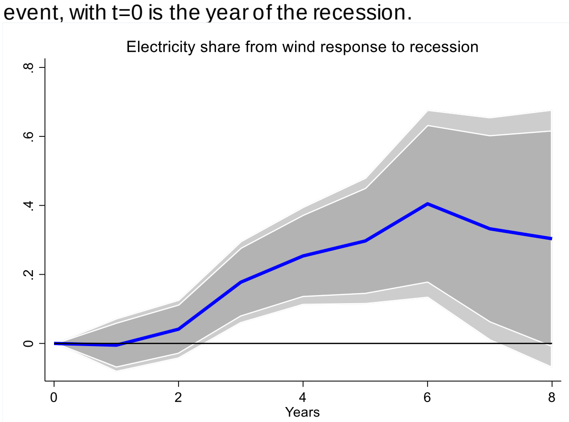
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



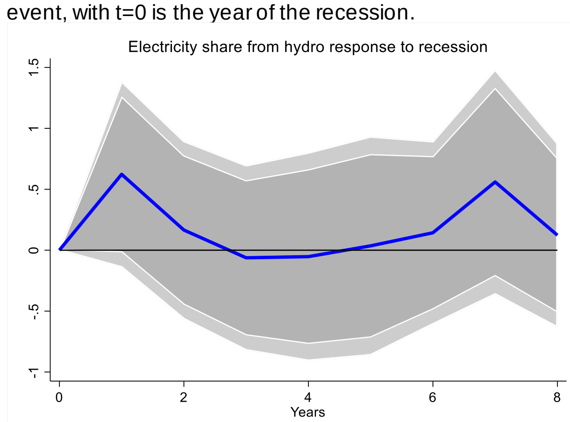
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

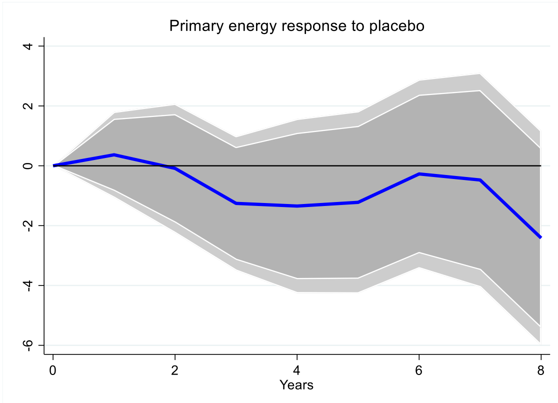


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

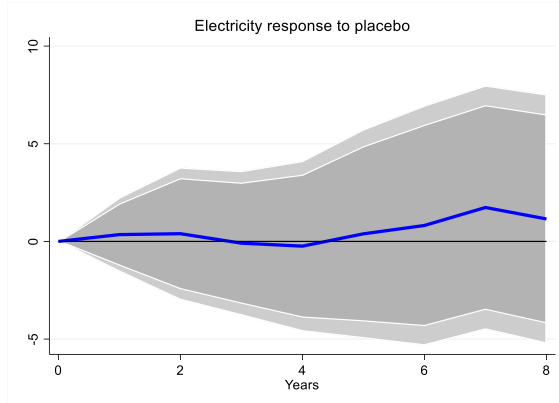


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

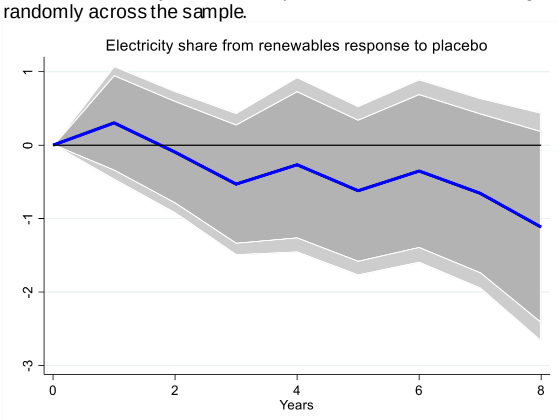
Figure 13. Robustness – Placebo and parallel trends



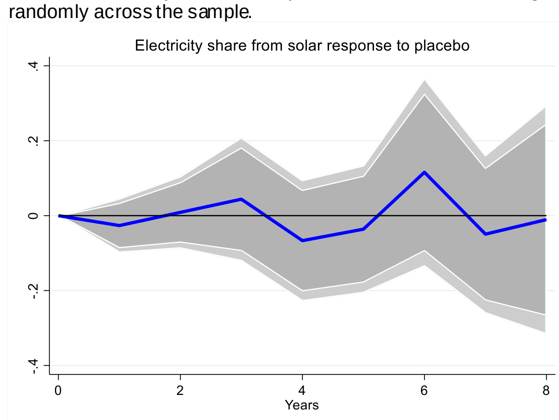
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the placebo event – a shock assigned randomly across the sample.



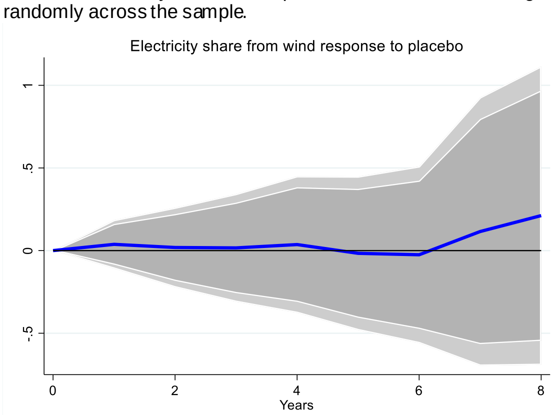
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the placebo event – a shock assigned randomly across the sample.



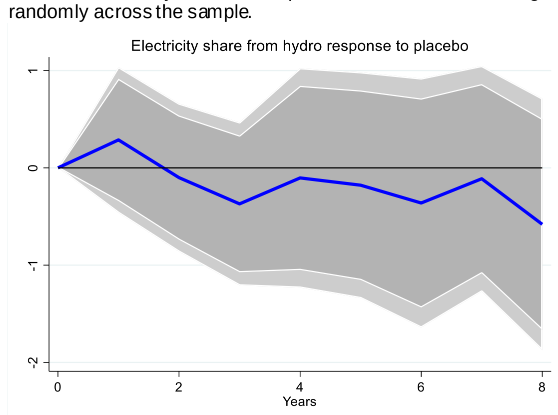
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the placebo event – a shock assigned randomly across the sample.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the placebo event – a shock assigned randomly across the sample.



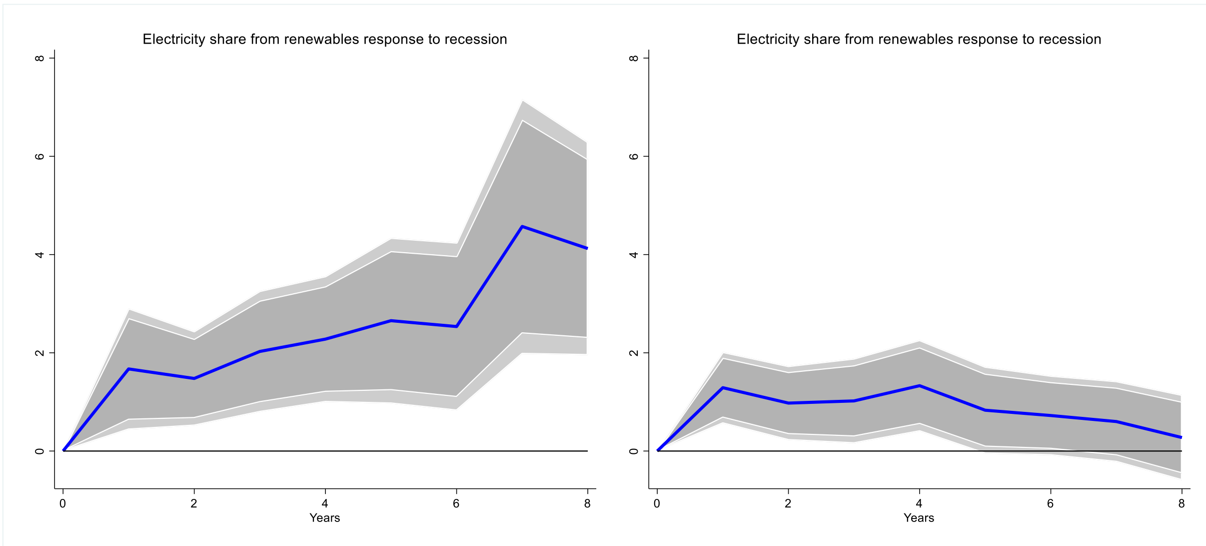
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the placebo event – a shock assigned randomly across the sample.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the placebo event – a shock assigned randomly across the sample.

Figure 14. Impact by type of economy

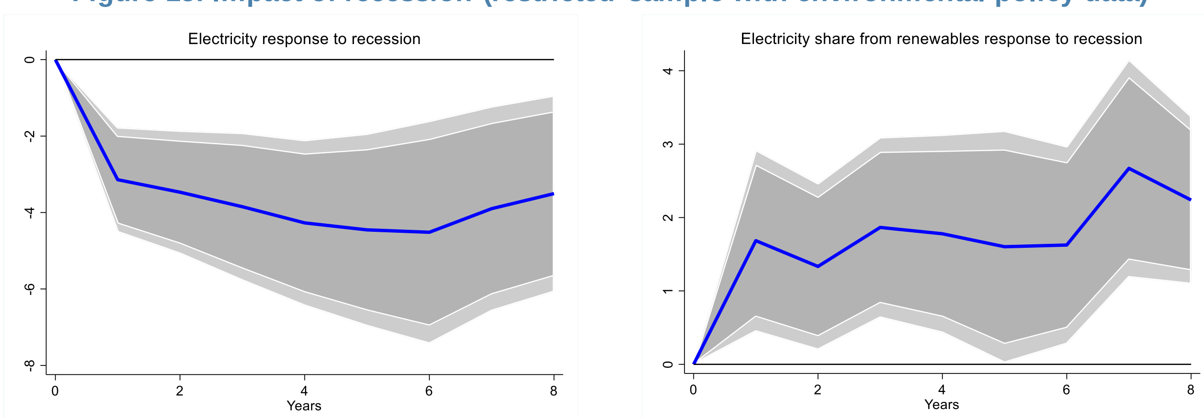
Advanced Economy *Emerging Market and Developing Economy*



Note: Impulse response functions are estimated over the period 1985–2019 using equation (1) for the subsample of 35 advanced economies. The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Note: Impulse response functions are estimated over the period 1985–2019 using equation (1) for the subsample of 135 emerging market and developing economies. The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

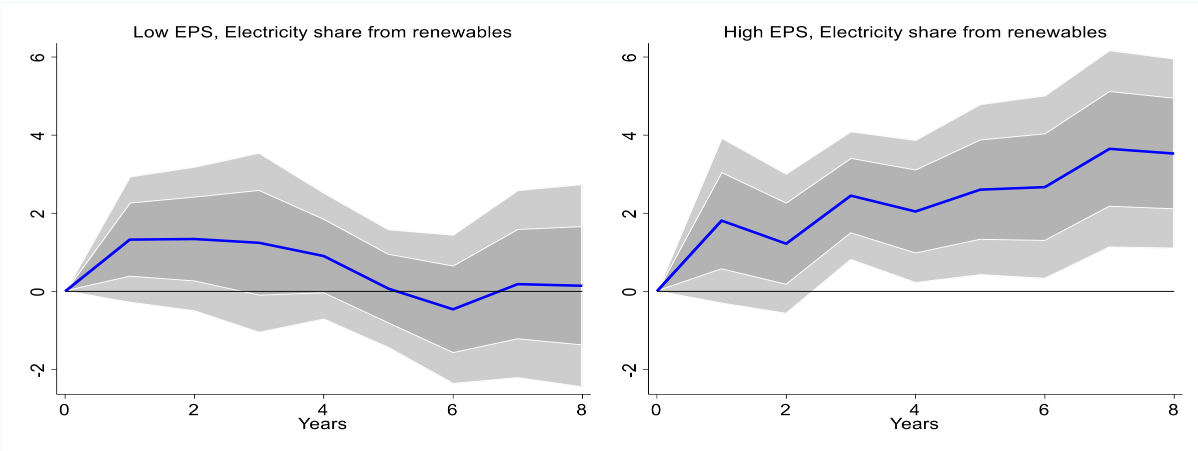
Figure 15: Impact of recession (restricted sample with environmental policy data)



Note: Impulse response functions are estimated using a sample of 33 countries over the period 1990–2015 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

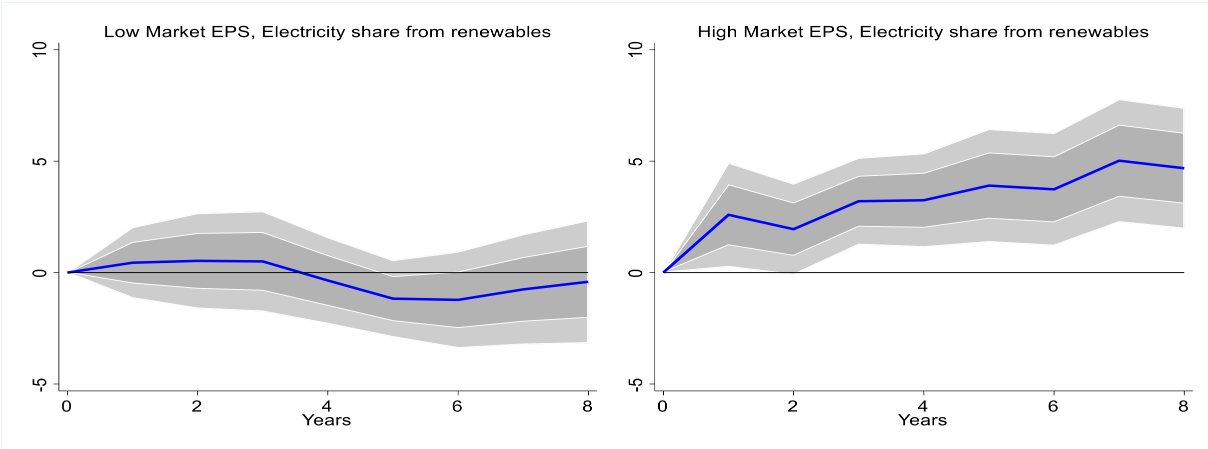
Note: Impulse response functions are estimated using a sample of 33 countries over the period 1990–2015 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Figure 16. Impact of environmental protection stringency (EPS)

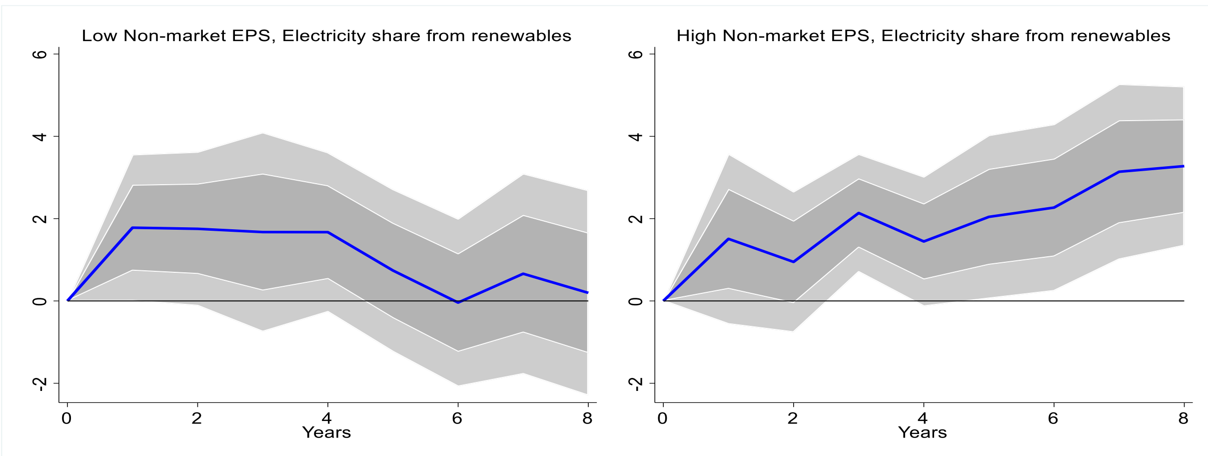


Note: Impulse response functions are estimated using a sample of 33 countries over the period 1990–2015 using equation (2). The graph shows the response and 95 and 90 percent confidence bands. The left panel denotes the low "regime" when $F(z_{it}) \approx 1$ and the right panel denotes the high `regime; when $(1 - F(z_{it})) \approx 1$. The x-axis shows years after the event, with t=0 is the year of the recession.

Figure 17. Impact by market vs non-market EPS

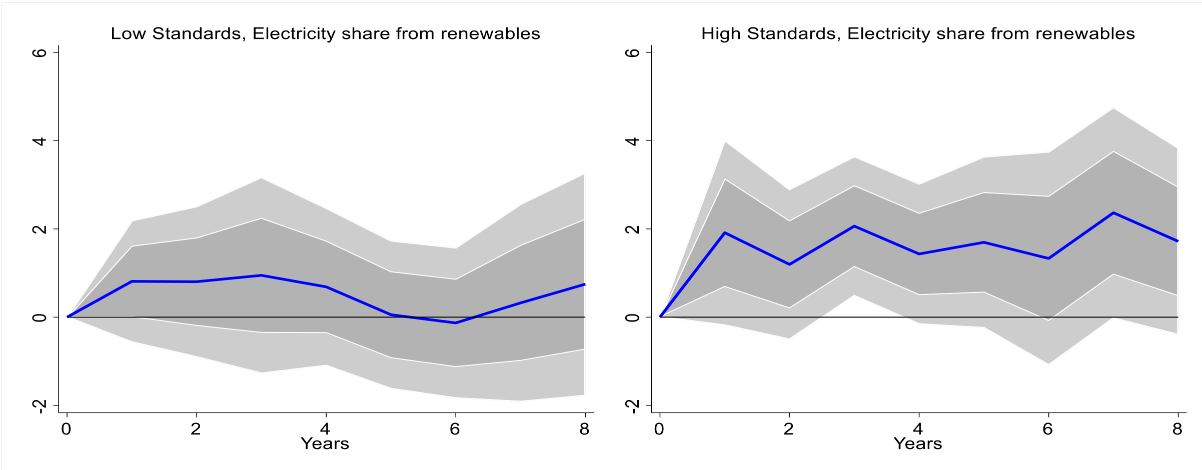


Note: Impulse response functions are estimated using a sample of 33 countries over the period 1990–2015 using equation (2). The graph shows the response and 95 and 90 percent confidence bands. The left panel denotes the low "regime" when $F(z_{it}) \approx 1$ and the right panel denotes the high `regime; when $(1 - F(z_{it})) \approx 1$. The x-axis shows years after the event, with t=0 is the year of the recession.

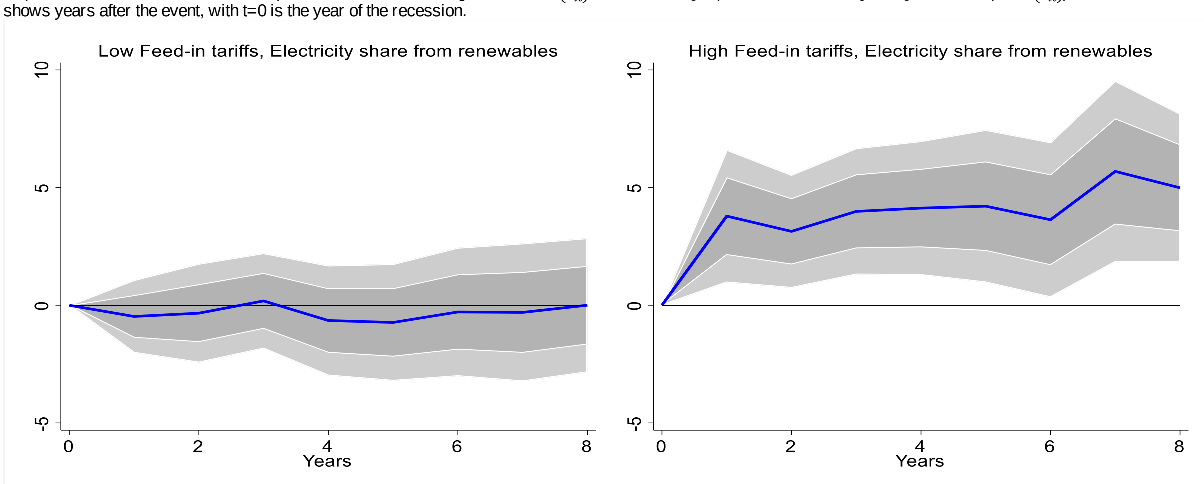


Note: Impulse response functions are estimated using a sample of 33 countries over the period 1990–2015 using equation (2). The graph shows the response and 95 and 90 percent confidence bands. The left panel denotes the low "regime" when $F(z_{it}) \approx 1$ and the right panel denotes the high `regime; when $(1 - F(z_{it})) \approx 1$. The x-axis shows years after the event, with t=0 is the year of the recession.

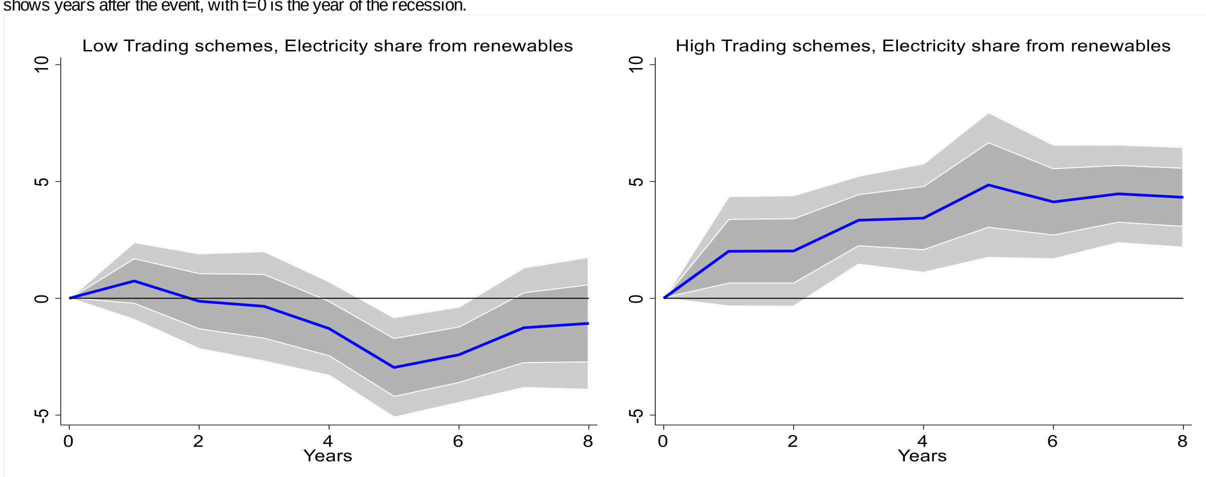
Figure 18. Impact of specific measures: Standards, feed-in-tariffs and trading schemes



Note: Impulse response functions are estimated using a sample of 131 countries over the period 1985–2016 using equation (2). The graph shows the response and 95 and 90 percent confidence bands. The left panel denotes the low "regime" when $F(z_{it}) \approx 1$ and the right panel denotes the high `regime; when $(1 - F(z_{it})) \approx 1$. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 131 countries over the period 1985–2016 using equation (2). The graph shows the response and 95 and 90 percent confidence bands. The left panel denotes the low "regime" when $F(z_{it}) \approx 1$ and the right panel denotes the high `regime; when $(1 - F(z_{it})) \approx 1$. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 131 countries over the period 1985–2016 using equation (2). The graph shows the response and 95 and 90 percent confidence bands. The left panel denotes the low "regime" when $F(z_{it}) \approx 1$ and the right panel denotes the high `regime; when $(1 - F(z_{it})) \approx 1$. The x-axis shows years after the event, with t=0 is the year of the recession.

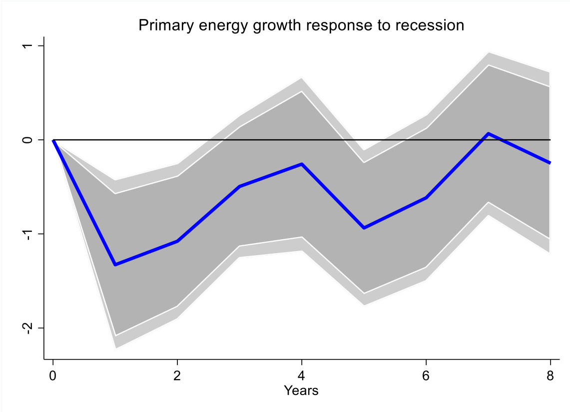
Table 1. Electricity share from renewables after recession

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	1 year	5 years	8 years	1 year	5 years	8 years	1 year	5 years	8 years
Recession	0.0138**	0.0136*	0.0174***	0.0147**	0.0153**	0.0212***	0.0145**	0.0149**	0.0165***
	(0.00606)	(0.00669)	(0.00530)	(0.00630)	(0.00679)	(0.00551)	(0.00584)	(0.00677)	(0.00551)
Lag 1	0.00321	0.00675	0.00463	0.00275	0.00774	0.00833	0.00258	0.00556	0.00464
	(0.00275)	(0.00546)	(0.00383)	(0.00270)	(0.00536)	(0.00503)	(0.00298)	(0.00599)	(0.00366)
Lag 2	0.00442	0.00741*	0.00466	0.00474	0.00786*	0.00716	0.00462	0.00803*	0.00614
	(0.00445)	(0.00402)	(0.00775)	(0.00459)	(0.00386)	(0.00902)	(0.00447)	(0.00426)	(0.00742)
Renewable share (Lag 1)	0.436***	0.365***	0.261	0.464***	0.445***	0.339*	0.441***	0.365***	0.251
	(0.103)	(0.113)	(0.180)	(0.103)	(0.125)	(0.195)	(0.105)	(0.113)	(0.177)
Lag 2	0.393***	0.427***	0.362	0.407***	0.448***	0.385	0.385***	0.402***	0.344
	(0.0848)	(0.128)	(0.232)	(0.0879)	(0.143)	(0.256)	(0.0829)	(0.122)	(0.225)
Overall EPS (Lag 1)	0.00290	0.0277***	0.0485***						
	(0.00449)	(0.00569)	(0.00982)						
Lag 2	0.0153***	0.0174***	0.0124*						
	(0.00538)	(0.00551)	(0.00660)						
Market EPS (Lag 1)				0.00507**	0.0239***	0.0378***			
				(0.00242)	(0.00635)	(0.00837)			
Lag 2				0.0120***	0.0176**	0.0164***			
				(0.00295)	(0.00651)	(0.00575)			
Non-market EPS (Lag 1)							0.00427	0.0207***	0.0343***
							(0.00423)	(0.00483)	(0.00625)
Lag 2							0.00957**	0.0148***	0.0141***
							(0.00460)	(0.00447)	(0.00387)
Constant	0.0177	0.00345	0.0380	0.0178	0.00615	0.0498	0.0182	0.00719	0.0401
	(0.0203)	(0.0487)	(0.0814)	(0.0216)	(0.0535)	(0.0883)	(0.0196)	(0.0475)	(0.0799)
Observations	708	692	627	708	692	627	714	698	633
R-squared	0.609	0.601	0.500	0.594	0.540	0.407	0.603	0.587	0.489
Number of countries	33	33	33	33	33	33	33	33	33

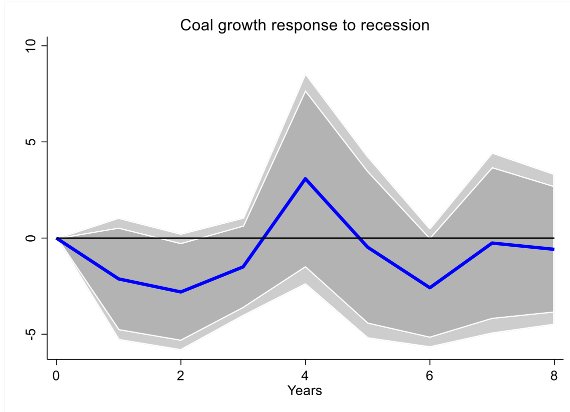
Dependent variable is the share of renewables in electricity generation. Robust standard errors clustered at the country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Annex I. Figures

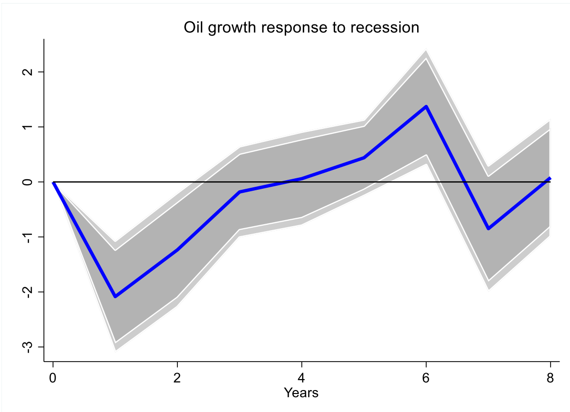
Annex Figure 1. Impact of recessions on growth in energy use



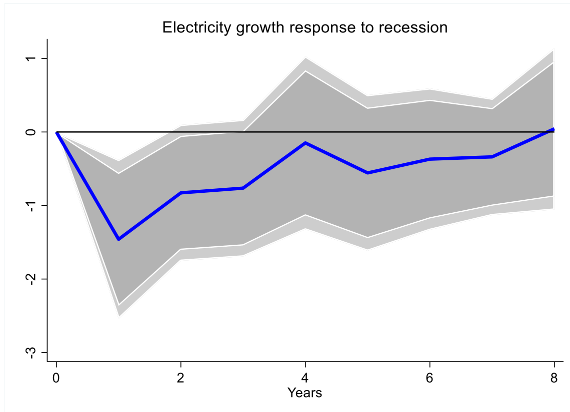
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

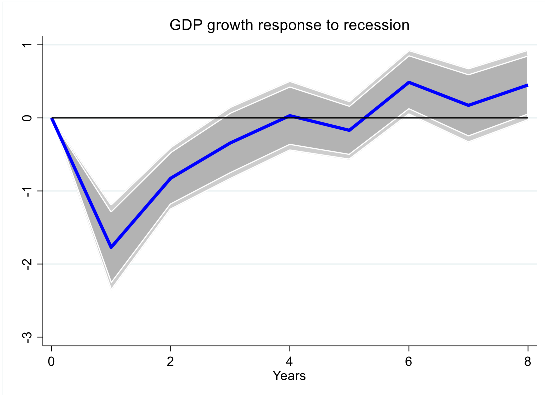


Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

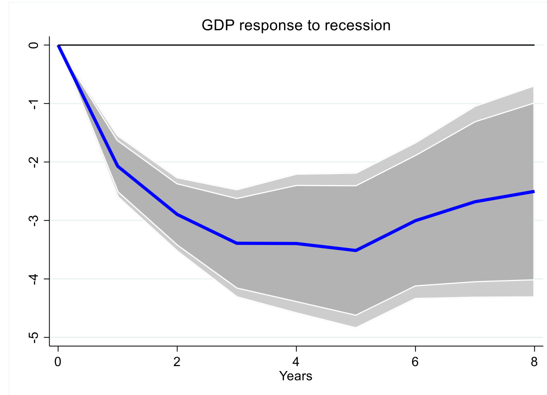


Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Annex Figure 2. GDP growth and level after recession

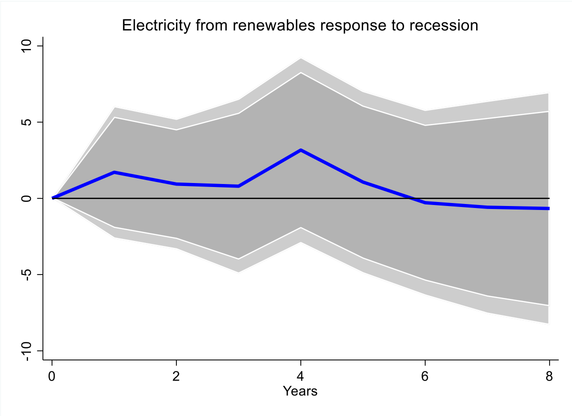


Note: Impulse response functions are estimated using a sample of 180 countries over the period 1982–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

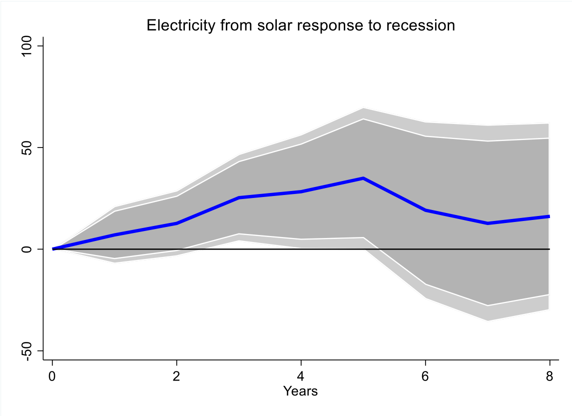


Note: Impulse response functions are estimated using a sample of 180 countries over the period 1982–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

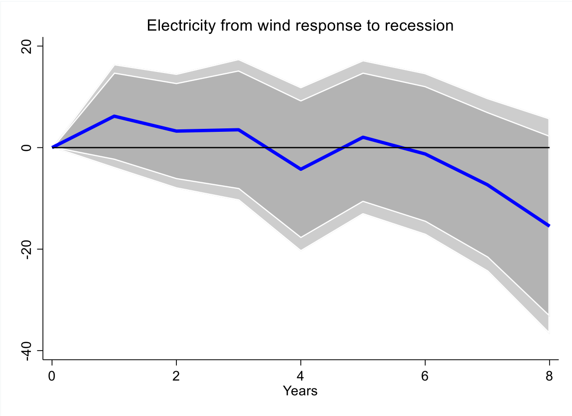
Annex Figure 3. Changes in level of renewables after recession



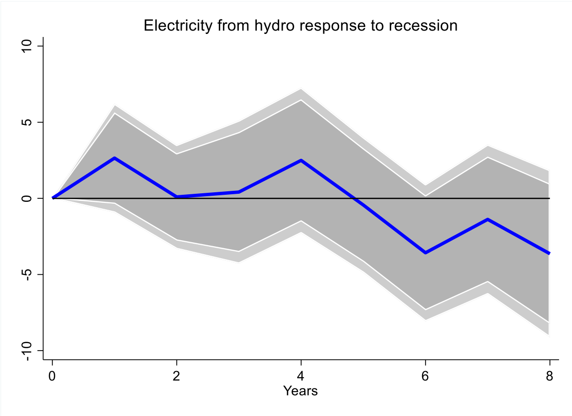
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

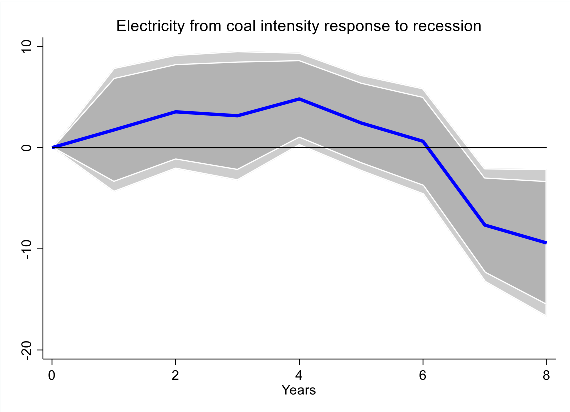


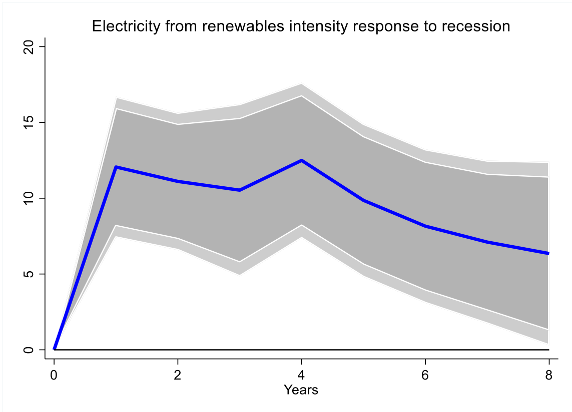
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Annex Figure 4. Energy intensity after recession

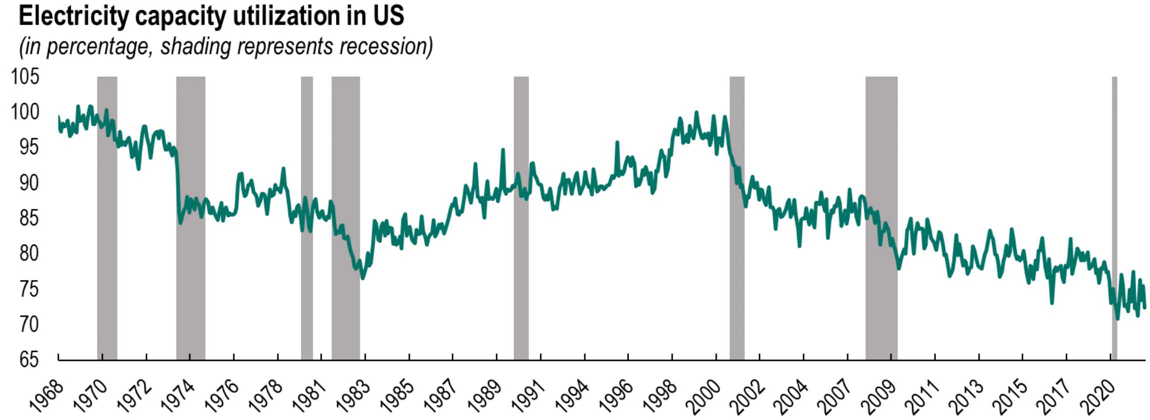




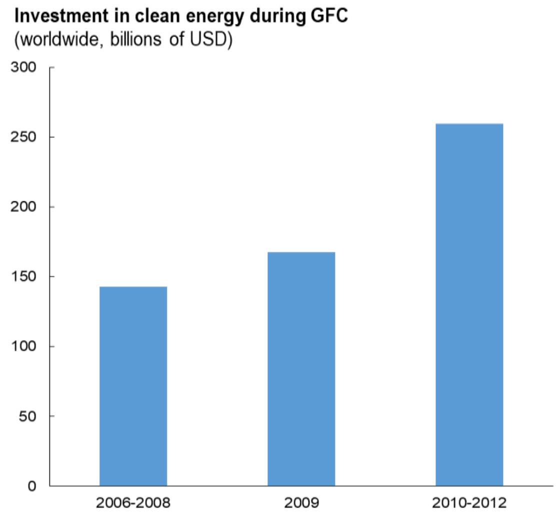
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

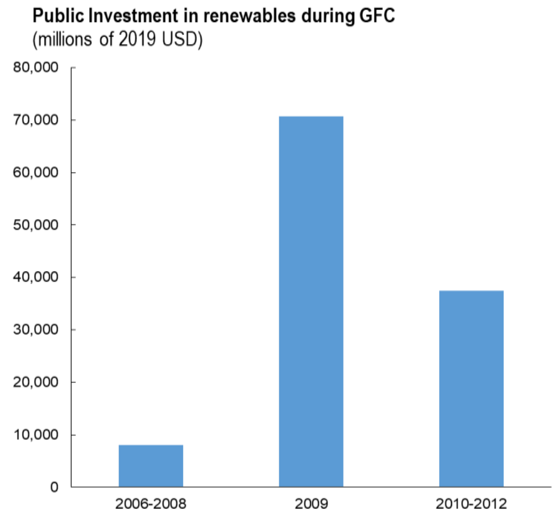
Annex Figure 5. Capacity utilization and investment during recessions



Source: Board of Governors of the Federal Reserve System (US), Federal Reserve Bank of St. Louis

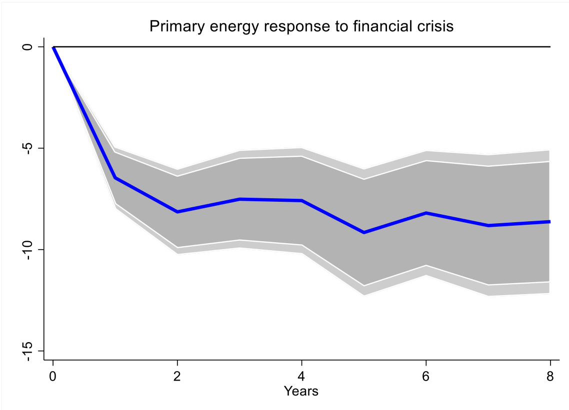


Source: Bloomberg; UNEP; FS-UNEP Collaborating Centre

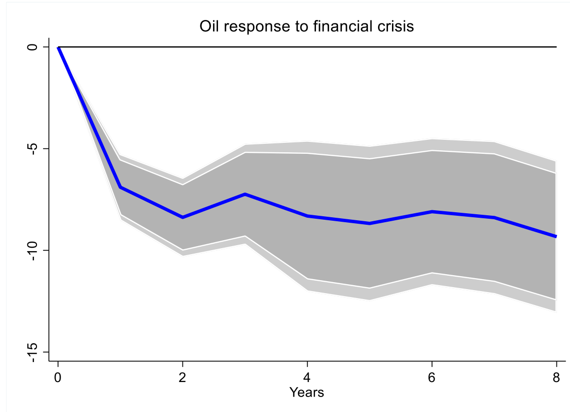


Source: The International Renewable Energy Agency (IRENA).

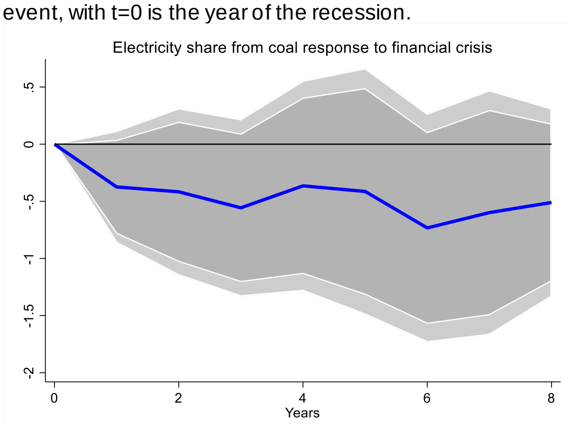
Annex Figure 6. Impact of financial crisis



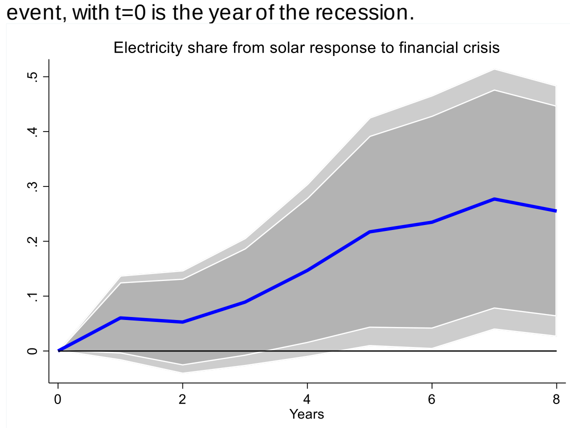
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



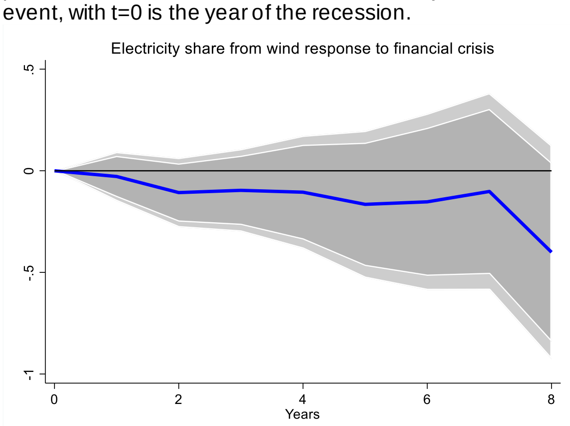
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



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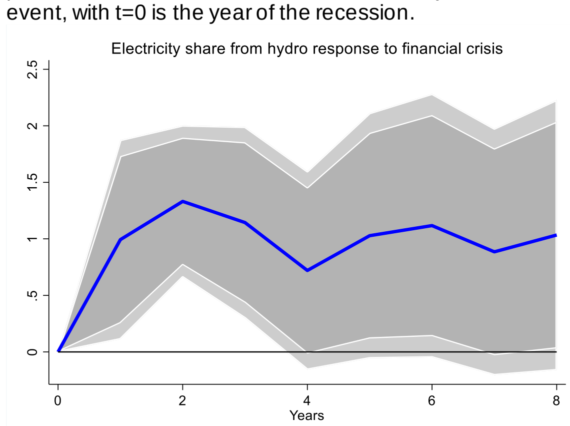
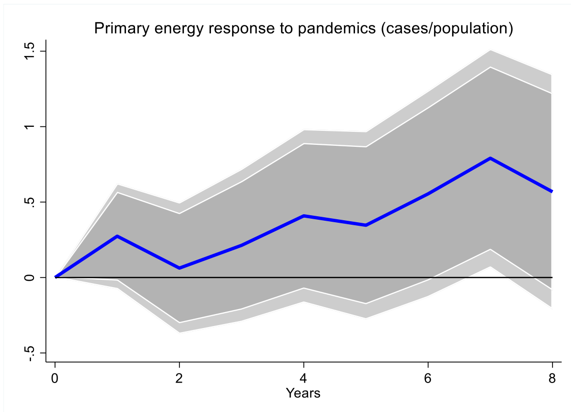
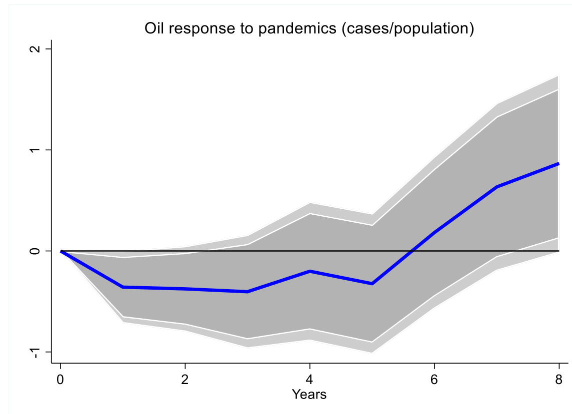


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

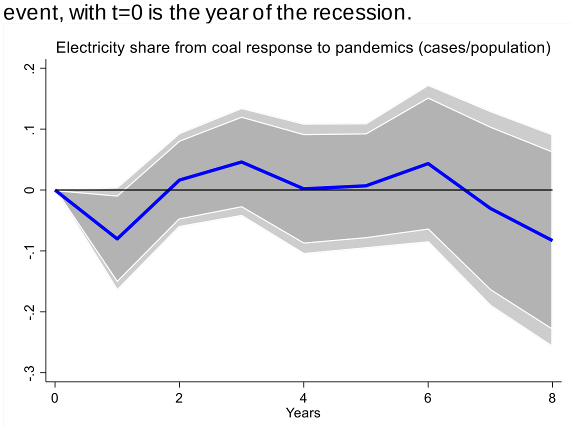
Annex Figure 7. Impact of pandemics (cases/population)



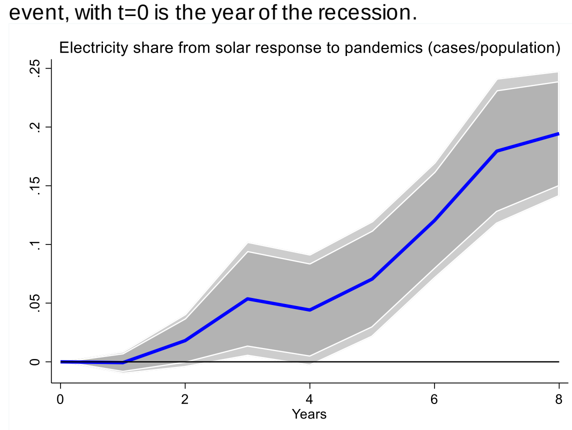
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



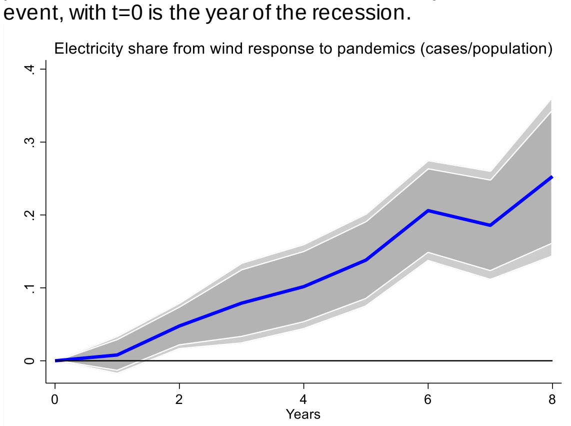
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



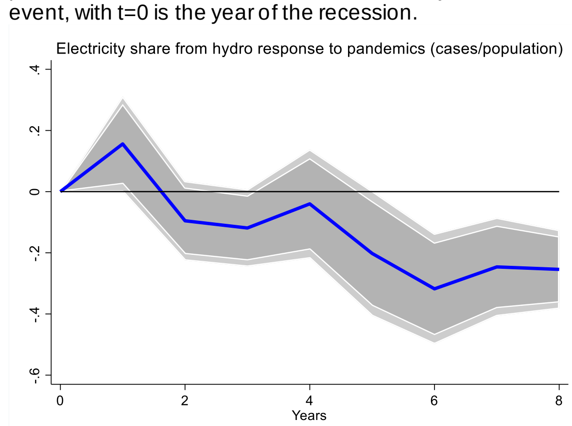
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

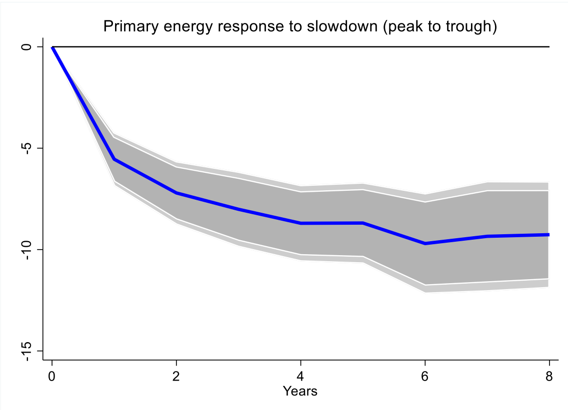


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

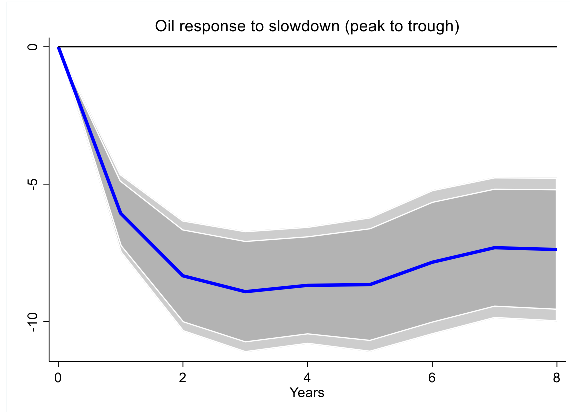


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

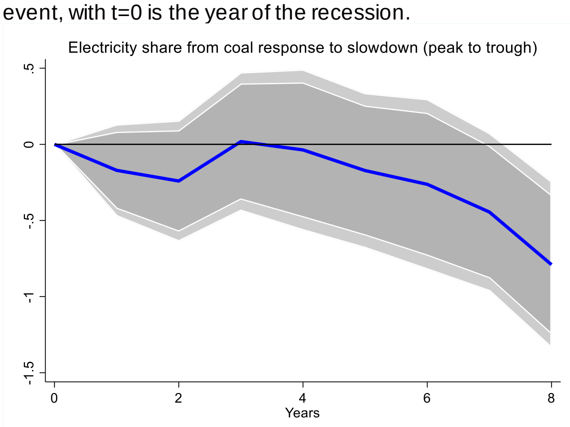
Annex Figure 8. Impact of growth slowdown (peak to trough)



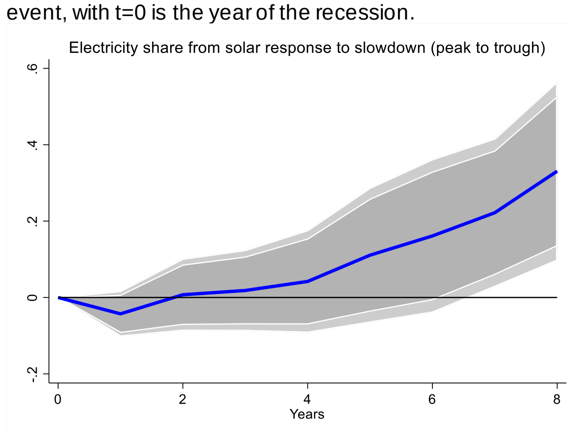
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



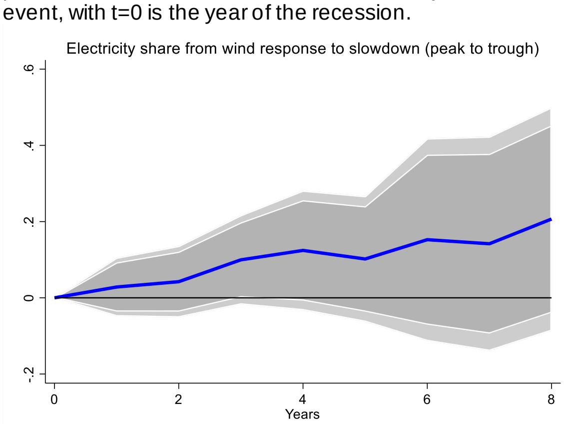
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



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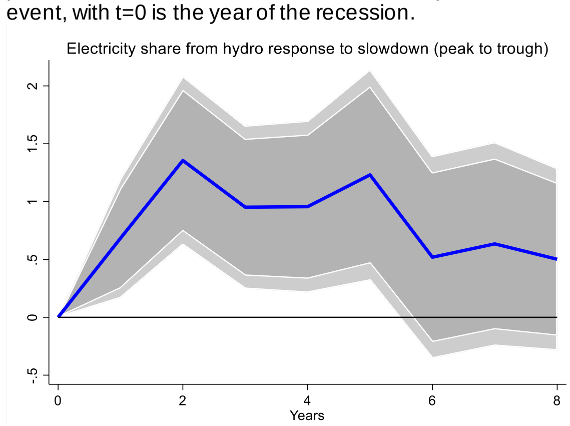
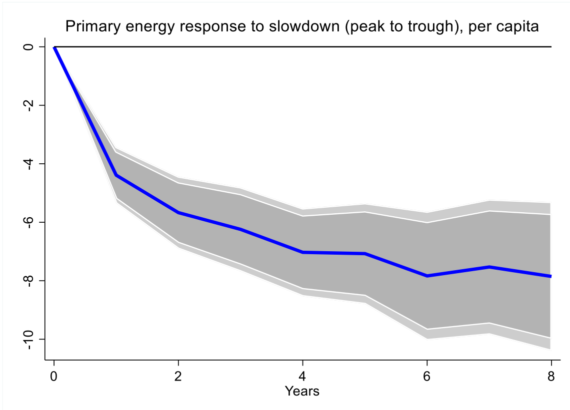
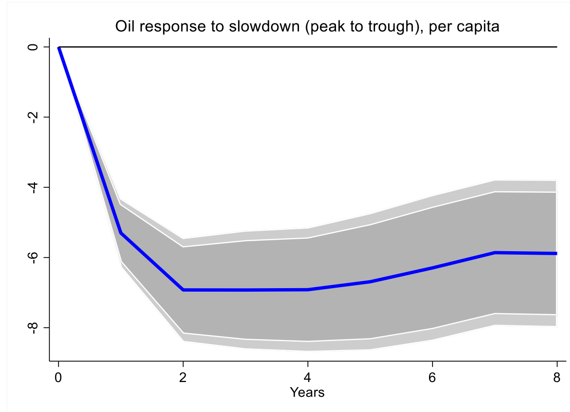


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

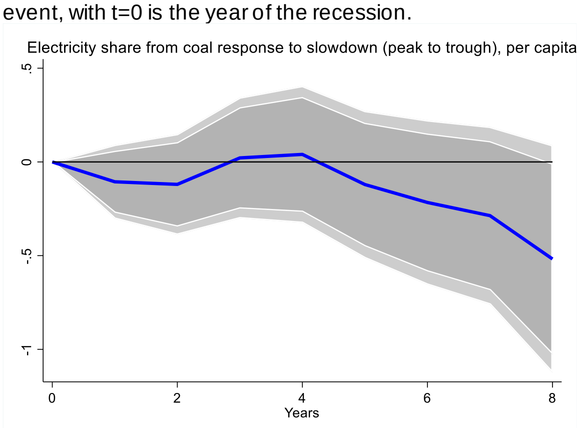
Annex Figure 9. Impact of per capita growth slowdown (peak to trough)



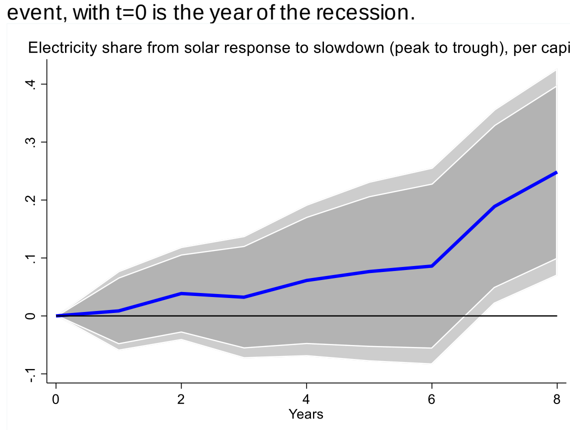
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



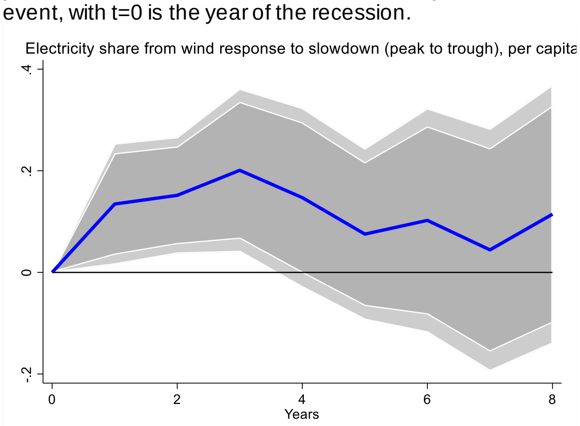
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



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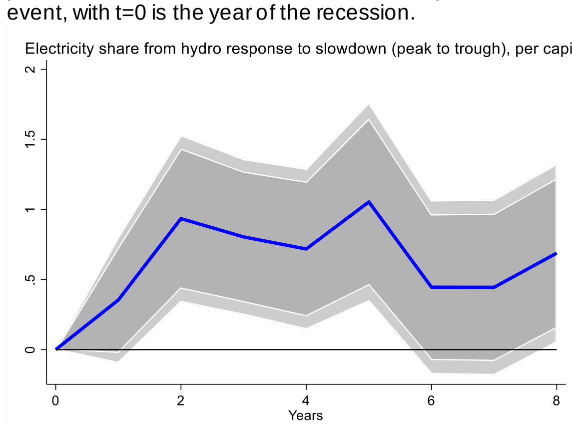
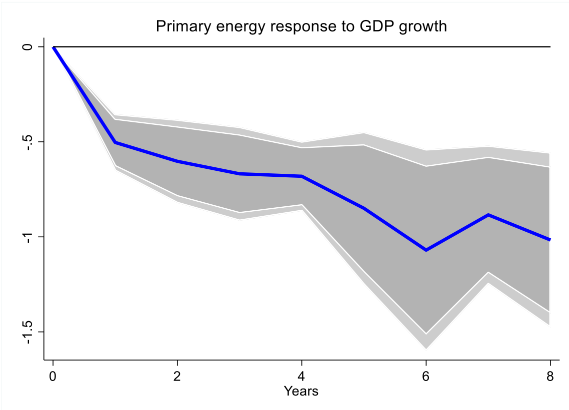
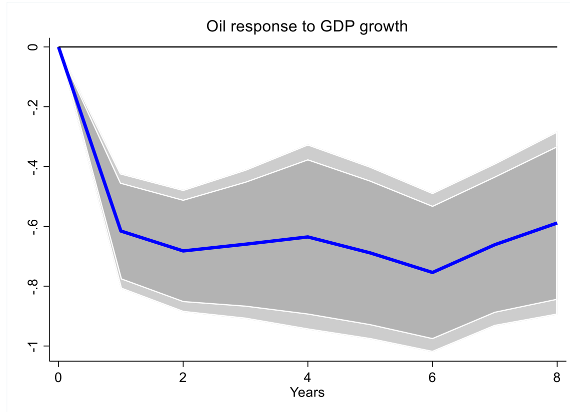


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

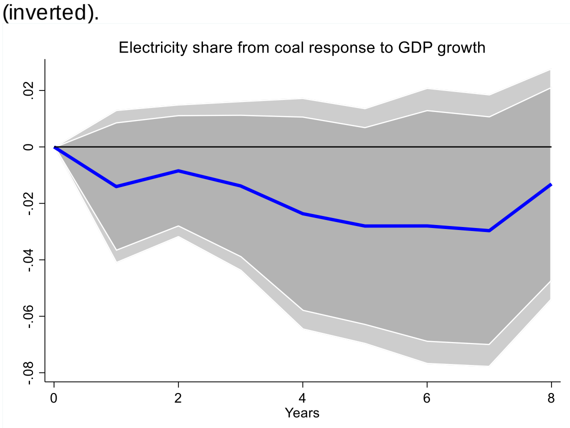
Annex Figure 10. Impact of GDP growth



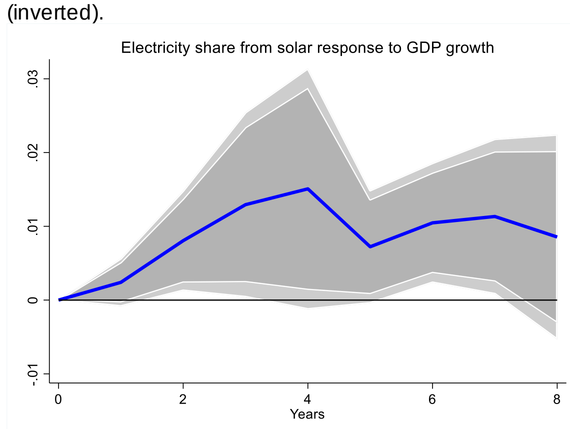
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).



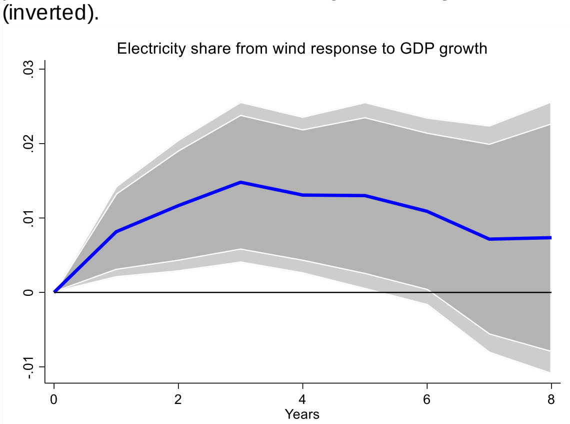
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).



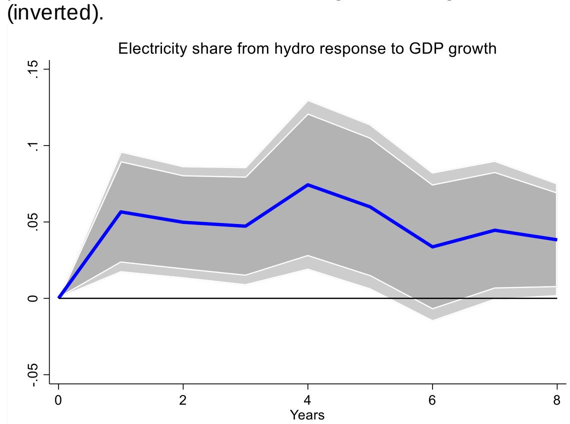
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).

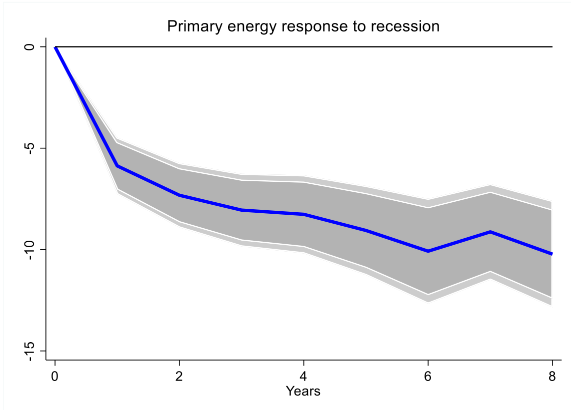


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).

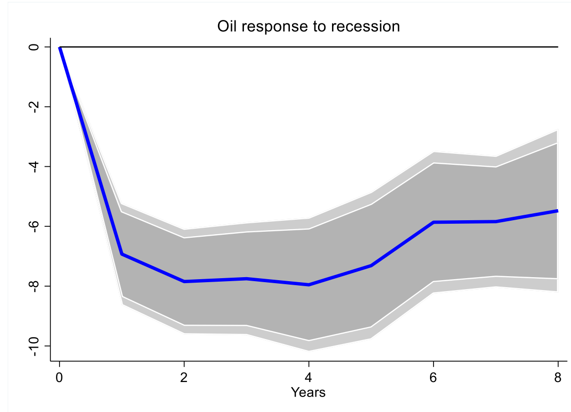


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands to changes in GDP growth (inverted).

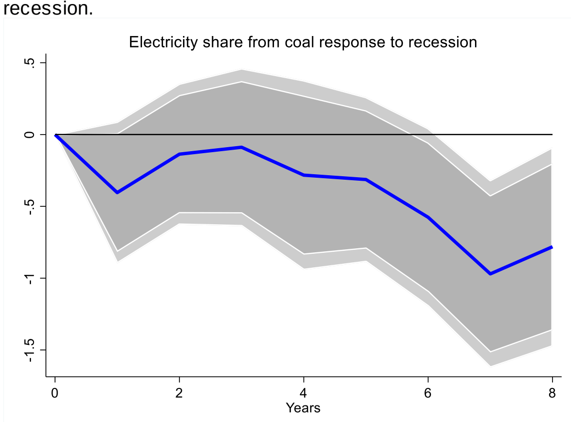
Annex Figure 11. Controlling for GDP growth directly (additional results)



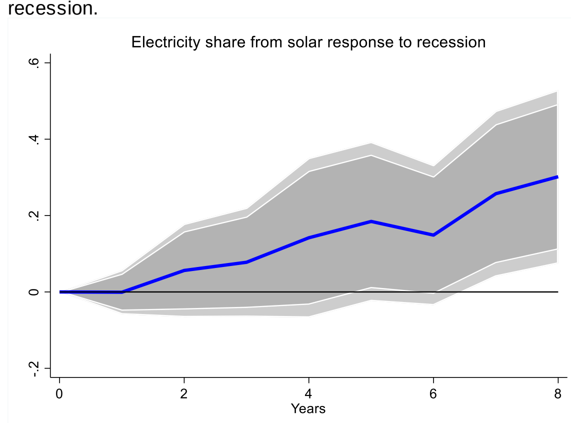
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



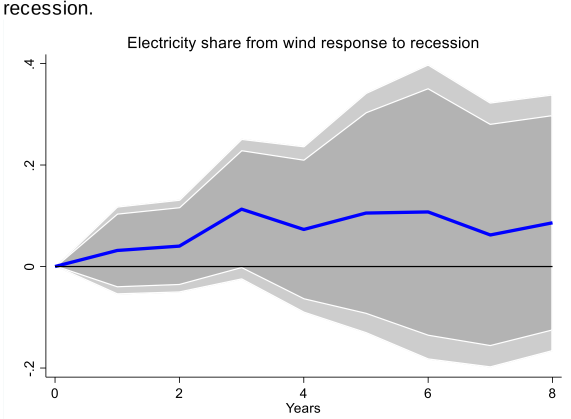
Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



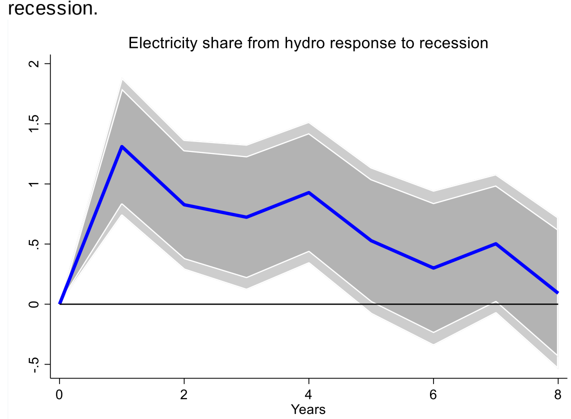
Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

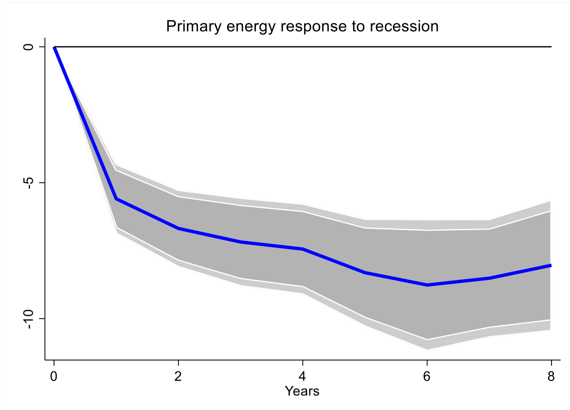


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

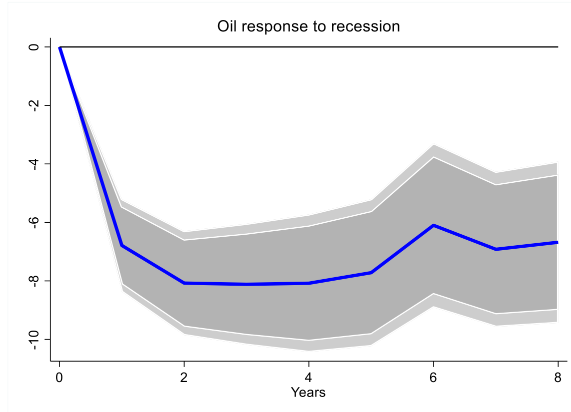


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Annex Figure 12. Time dummies (additional results)



Note: Impulse response functions are estimated using a sample of 176 countries over the period 1965–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



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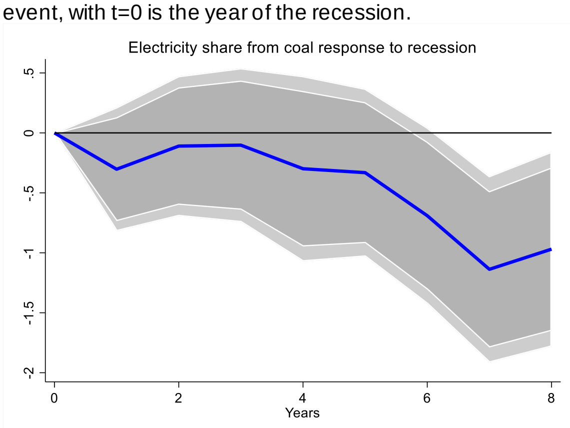

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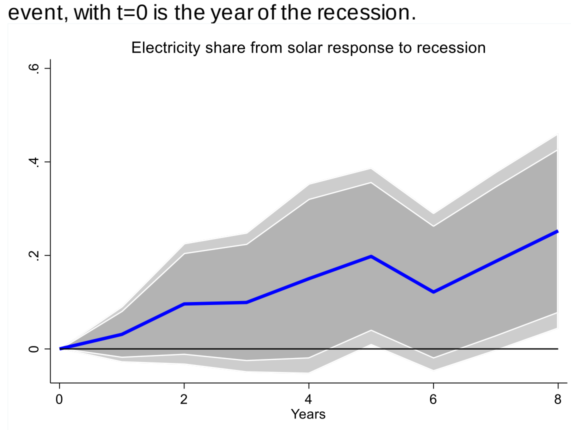

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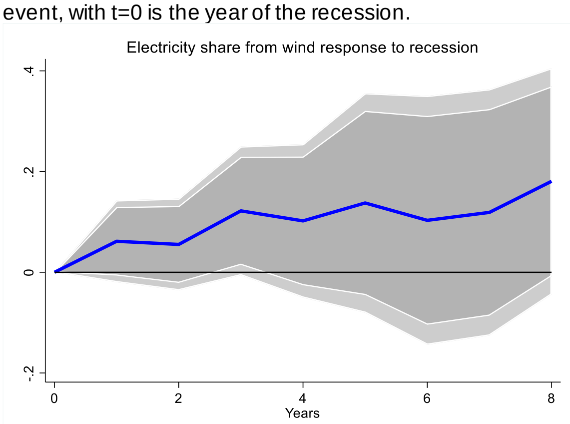

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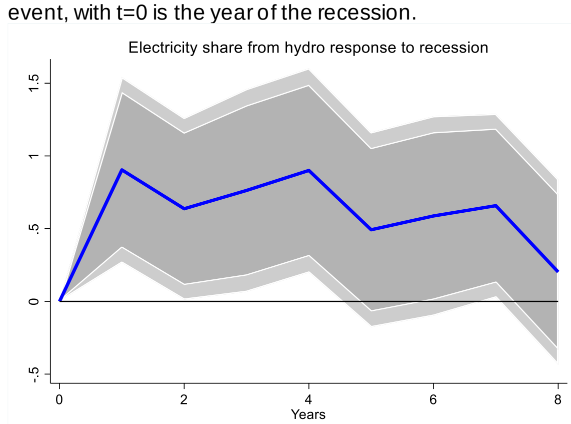
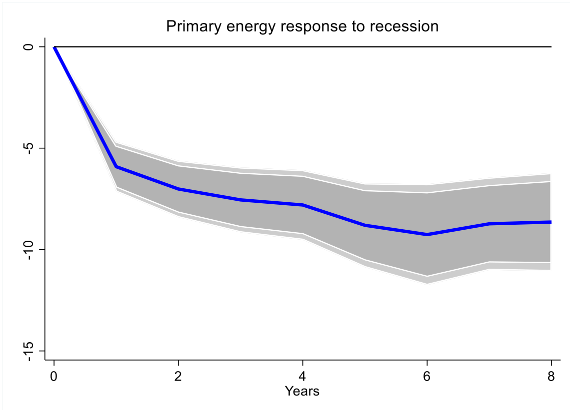


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

Annex Figure 13. Time trends (additional results)



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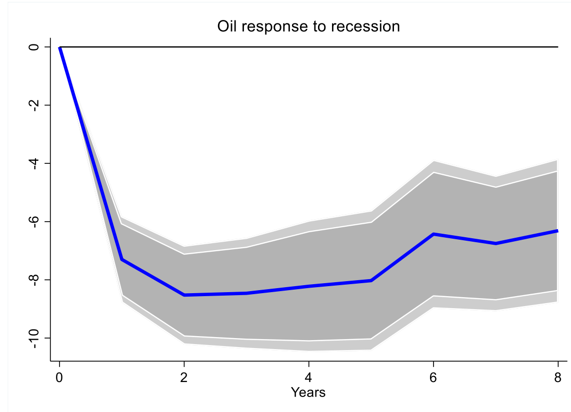

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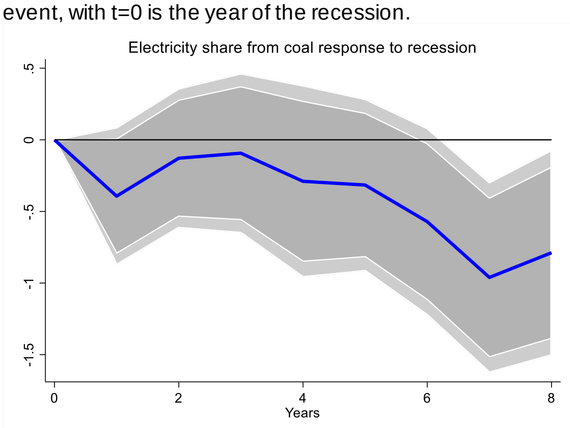
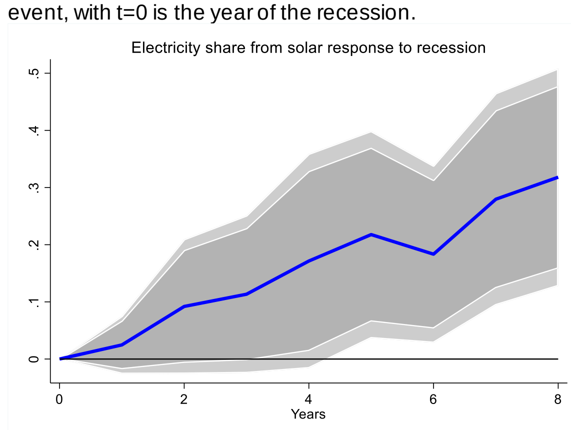


Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.



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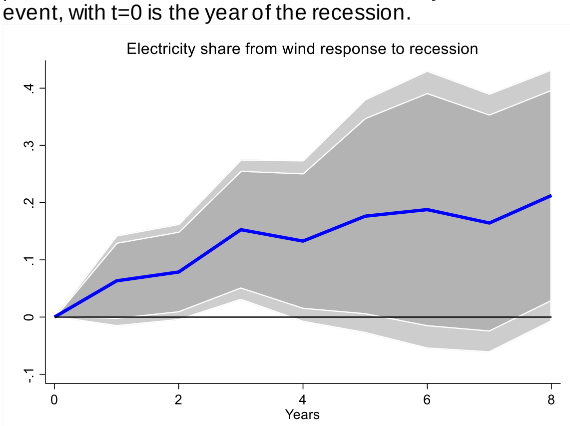

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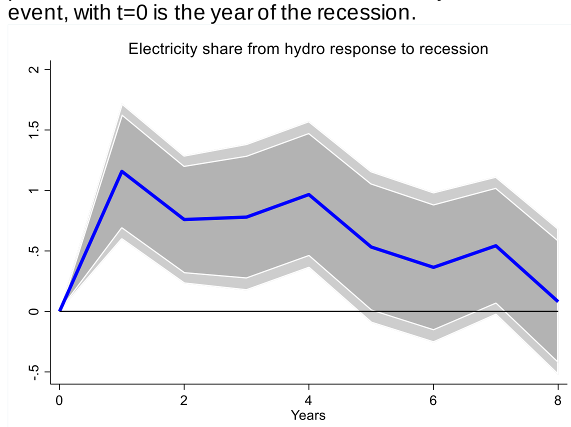

Note: Impulse response functions are estimated using a sample of 172 countries over the period 1985–2019 using equation (1). The graph shows the response and 95 and 90 percent confidence bands. The x-axis shows years after the event, with t=0 is the year of the recession.

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