CHAPTER 3

ONLINE ANNEX

Annex 3.1. The Impact of Environmental Policy on Clean Innovation

This note describes the empirical model and the data and presents more detailed results on the influence of climate mitigation policies on innovation in climate mitigation technologies. It starts with a selective presentation of the most closely related papers, followed by a brief explanation of the conceptual basis and the estimation strategy, before introducing the key variables and the main results.

Related Literature

The most closely related paper to this analysis is Johnstone and others (2010).[1] Similar to our paper, it analyses in a cross-country setup the effect of broad policy measures on climate-change mitigating innovation. Our analysis however benefits from a much more recent sample,[2] a more precise technological classification and more standardized policy indicators, namely the environmental policy stringency (EPS) indicator published by the OECD.[3] This allows us to better capture the dramatic increase in clean innovation of the early 2000s, but also the flattening and partial reversal since 2010.[4] Our analysis relies on the environment-related technology (ERT) classification proposed by Haščič and Migotto (2015). However, rather than relying on all ERT technologies, we focus on the climate change mitigation technologies related to energy. These are among the technologies with the biggest potential for emissions reductions and most closely targeted by climate-related policies. Unlike the technologies investigated by Johnstone and others (2010), they include not only renewable energy, but also technologies related to improved efficiency in energy generation, transmission and distribution. In addition, we use a technological specification proposed by Dechelepretre and others (2017) to look more closely at technologies related to electricity. The classification has the advantage of not only identifying clean technologies, but also dirty as well gray one, where the latter are innovation that improve the environmental impact of dirty technologies (e.g. biofuel, waste incineration plants). This allows us to study the relative benefits from tightening environmental policies for these different types of technologies, as well as the impact on electricity innovation overall.

[1] Other relevant papers using cross-country analysis of similar questions include Popp (2006) and De Vries and Withagen (2005).

[2] The sample in Johnstone and others (2010) is limited to 25 countries over the time frame of 1978-2003, while our sample covers 33 countries from 1990-2015.

[3] OECD (2018), "Environmental Policy Stringency index (Edition 2017)", OECD Environment Statistics (database), https://doi.org/10.1787/b4f0fdcc-en (accessed on 28 July 2020).

[4] For a discussion of possible reasons behind the relative decline in clean innovation post-2010, see Popp and others (2020) and Acemoglu and others (2019). Among a partial relaxation in environmental standards in some countries, technological progress especially related to hydraulic fracturing, energy prices and reduced investor appetite after a possible technology bubble in the previous years may have diminished returns to clean research.

Conceptual Framework

The conceptual basis for the empirical estimation is a multiplicative production function of new innovation in country i in technology j along the lines of the one specified in Acemoglu and others (2016).

$$X_i^j = \theta \left(H_i^j\right)^{\beta} \left(u_i^j\right)^{\gamma}$$

where u_i^j stands for the accessible stock of knowledge and H_i^j stands for the research effort. The equation can be re-written as an equation that can be estimated with empirical count models.

$$X_i^j = \exp\left(\alpha + \beta \ln\left(H_i^j\right) + \gamma \ln\left(u_i^j\right) + \epsilon_i^j\right)$$

where $\alpha = \ln(\theta)$ and ϵ_i^j is the residual. Acemoglu and others (2016) assume that new innovation X_i^j follows a Poisson distribution.

In our empirical estimation, the flow of innovation X_i^j is proxied by the number of climate change mitigating patent families associated with a particular country, and where the first patent application was made in a given year. A patent family is associated with a given country if it is the most common country of residence of the first inventors of the different patents.

The key line of investigation is how environmental policy affects the flow of innovation. Consistent with the conceptual framework, the baseline includes the stock of knowledge[5] as well as overall innovation. The latter controls for policies related to education and research as well as changing patenting cultures.[6] In addition, the model includes both country- as well as year fixed effects, to control for time-invariant country characteristics, as well as global dynamics, including the effects of the global business cycle. The year fixed effects also capture the influence of changes in the oil prices as well as part of the common trend towards tighter environmental standards. In a subsequent analysis of the fixed effects, we try to shed light on the relative importance of these two factors in driving the global trends. The equation is estimated using the fixed effects Poisson estimator with clustered robust standard errors, in line with today's best practices. All control variables are lagged by one year, as they are in part pre-determined (e.g., the knowledge stock) and to account for time lags in knowledge production.

[5] The inclusion of the stock of knowledge creates an indirect link between policies and innovation as a higher effort u_f^j today creates a bigger knowledge stock tomorrow H_f^j, which provides a bigger base for innovation in the future. The patent stock in the specific ERT technology is constructed using the perpetual inventory method. The 1965-1975 growth rate in patenting, a 10 percent annual depreciation rate and a geometric series are used to determine the stock in 1965. If the depreciation rate is $\sigma = 0.1$ and δ is the annual growth rate in patenting, the initial stock $S_{1965} = \frac{1}{1-r} P_{1965}$, where $r = (1-\sigma)/(1+\delta)$ and P_{1965} the initial level of patenting.

[6] The incentives to patent a given technology differ across countries, but also change over time. For example, patent promotion policies in China or the historical requirement in Japan to have a separate application for each claim have resulted in a relative inflation in the numbers of applications in some countries. The inclusion of overall patenting controls for such differences.

Main Results

The table below shows the main results (Annex Table 3.1.1). The effect of the aggregate EPS indicator is reasonably stable across specifications and highly statically significant. In the various columns, the different specifications control respectively for the evolution of oil and gas reserves, the electricity prices at the household level, as well as indicators for labor and electricity market regulation. The control variables have the expected sign and are often statistically significant. As the inclusion of additional controls rapidly reduces the size of the sample, column 1 is used to calculate illustrative examples. Its coefficient of the EPS variable is at the lower end of the range over the different specifications. The illustrations below would thus produce stronger effects, if the we relied on a specification with additional controls.

Annex Table 3.1.1. Aggregate Effect of Environmental Policy on Clean Innovation

Dependent variable: CCM energy patent families	(1)	(2)	(3)	(4)	(5)	(6)
EPS_{t-1}	0.174***	0.237***	0.179***	0.223***	0.154***	0.201***
	(4.05)	(5.04)	(5.50)	(5.62)	(4.40)	(5.33)
Log tech $stock_{t-1}$	0.551***	0.581***	0.455***	0.444***	0.486***	0.264*
	(11.63)	(5.39)	(10.28)	(3.69)	(8.06)	(1.80)
Log all $tech_{t-1}$	0.468***	0.473***	0.656***	0.704***	0.286**	0.640***
	(9.09)	(4.56)	(8.85)	(6.12)	(2.46)	(3.45)
Log oil and gas reserves $(bb)_{t-1}$		-0.111		-0.0596		-0.0837
		(1.25)		(0.49)		(0.70)
Price of electricity for households $(USD)_{t-1}$			0.278***	0.252**		0.408***
			(3.35)	(2.19)		(3.86)
ETCR $electricity_{t-1}$					-0.0782**	-0.0669
					(2.02)	(1.28)
Labor market $regulation_{t-1}$					0.0143	-0.0276
					(0.60)	(0.89)
Number of observations	762	724	589	560	417	345

Source: IMF staff calculations.

Note: All regressions include country and year fixed effect. T-statistics in parentheses. EPS = environmental policy stringency; CCM = climate change mitigating; tech stock = patent stock in specific technology, all tech = total patenting in all technologies; bb = billions of barrels; ETCR = energy, transport and communication regulation. Data on labor market regulation is from the Economic Freedom of the World by the Fraser Institute.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

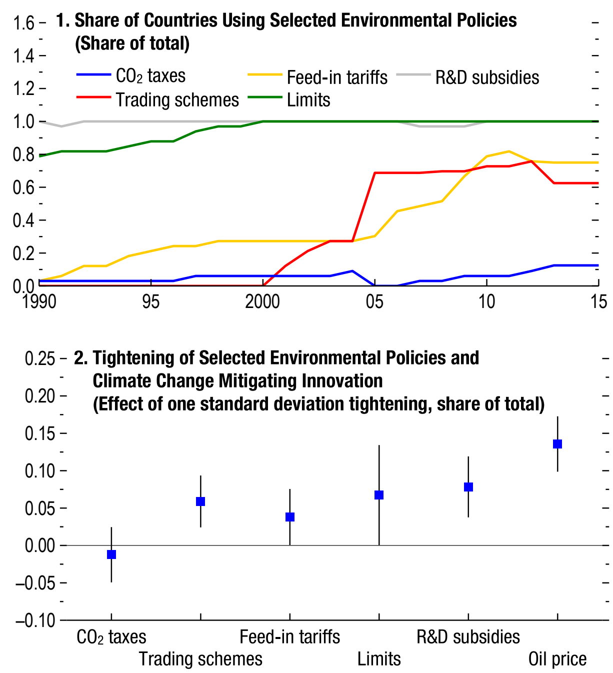
These effects are not only statistically, but also economically significant. To illustrate this, we compare the predicted level of innovation at the country level, ignoring the global components captured by the year fixed effects, with the same prediction if the EPS indicator had not changed since 1990. This comparison suggests that the change in the EPS directly contributed to roughly 30 percent of the increase in innovation between 1990 and 2010. Given that more innovation leads to a bigger knowledge stock, there would additionally be an indirect, second-round effect, whose magnitude would however be of second order.

By not including the fixed effects in the two predicted values, the above comparison remains consistent with the empirical estimation. It ignores however global factors such as oil prices and the common upward trend in environmental policy stringency. We thus investigate to what extent the year-FE have been driven by these two factors. For this, the retrieved year fixed effects from the baseline regression are regressed on the EPS indicator (country-specific) and oil prices. Based on this second regression we again compare the predicted year fixed effects with the actual EPS indicator and the predictions keeping either the EPS indicator or oil prices at 1990 levels. This suggests that the change in the EPS indicator is responsible for 37 percent of the increase between 1990 and 2010 in global innovation captured by year-FE. This is a significant share but only about half of the contribution from the increase in oil prices. The comparable, but somewhat bigger contribution from energy prices is confirmed by an analysis of the R^2. The individual contribution of the environmental tightening to the variation in the year fixed effects is about 30 percent, compared to an individual contribution of 46 percent from oil prices. The joint contribution of the two amounts to 61 percent.

The Effect of Individual Policies

Going beyond the aggregate EPS indicator, we investigate whether some specific policies are more important than others, using the EPS sub-indicators as the variable of interest. In the table below the policies are first included individually (Annex Table 3.1.2, columns 1 to 5). Column 6 assesses the impact of individual policies on clean innovation, controlling for all others (see also Annex Figure 3.1.1). Although, there has been some co-movement among individual policies, most coefficients barely change when other policies are controlled for. The results suggest that both non-market policies—such as emission limits and R&D subsidies—as well as market policies—such as trading schemes and feed-in tariffs—made a statistically significant contribution to clean innovation. The one major exception are carbon taxes, where the effect is insignificant. This result can be explained by the very limited use of this particular policy tool. While the other policy tools shown here were used by 60-100 percent of the countries in the sample, only slightly more than 10 percent of them used carbon taxes in 2015 (OECD 2018).

Annex Figure 3.1.1. Popularity and Effect of Individual Environmental Policies



Sources: International Energy Agency; Organisation for Economic Co-operation and Development; Worldwide Patent Statistical Database; and IMF staff calculations.
Note: Panel 2 shows the effect of one standard deviation change in policy indicator, conditional for all other policies (as in column 6). CCM innovation = patents in climate change mitigating technologies; R&D = research and development.

Annex Table 3.1.2. Effect of Individual Policies

Dependent variable: CCM Energy patent applications	(1)	(2)	(3)	(4)	(5)	(6)
Log tech stock$_{t-1}$	0.551***	0.531***	0.596***	0.543***	0.508***	0.519***
	(14.20)	(13.72)	(11.29)	(12.32)	(13.22)	(10.48)
Log all tech$_{t-1}$	0.492***	0.506***	0.438***	0.448***	0.593***	0.525***
	(9.28)	(10.40)	(7.16)	(10.23)	(12.66)	(9.71)
CO_2 taxes	0.0105					-0.016
	(0.47)					(0.55)
Trading schemes		0.0333**				0.0320***
		(2.03)				(2.79)
Feed-in tariffs			0.0278***			0.0207*
			(3.10)			(1.67)
Emission limits				0.0511**		0.0388*
				(2.29)		(1.65)
R&D subsidies					0.0693***	0.0616***
					(5.41)	(3.16)
Number of observations	788	785	788	788	788	785

Source: IMF staff calculations.

Note: All regressions include country and year fixed effect. T-statistics in parentheses. EPS = environmental policy stringency; CCM = climate change mitigating; tech stock = patent stock in specific technology, all tech = total patenting in all technologies.

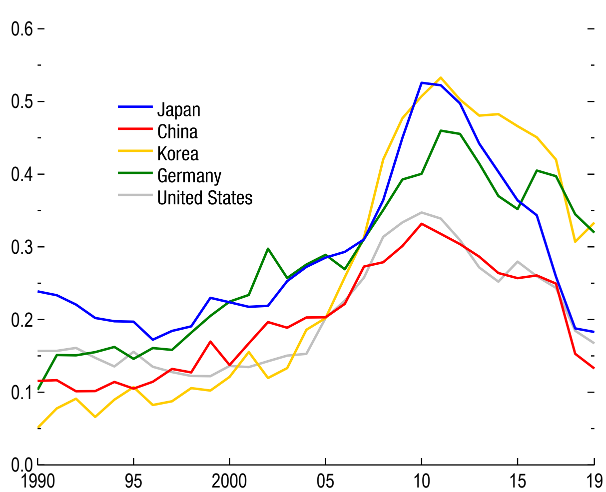
*** p<0.01, ** p<0.05, * p<0.1.

Clean, Gray, Dirty and Total Electricity Innovation

After focusing on specific policies, the next analysis looks at a particular set of technologies: electricity. The electricity sector is responsible for a significant share of global emissions and thus targeted by many environmental policies. In addition, focusing on electricity is interesting as, relying on a classification by Dechezlepretre and others (2017), we can distinguish clean electricity innovation from dirty and gray innovation, where gray innovations are technologies that improve the environmental impact of dirty technologies. The classification illustrates that the share of clean innovation in electricity-related technologies has increased dramatically up to about 2010 (Annex Figure 3.1.2). It also allows us to empirically assess the relative effect of policies on the different types of technologies as well the overall effect on electricity innovation.

Annex Figure 3.1.2. Share of Clean Electricity Innovation

(Share of total)



Sources: Dechezleprêtre, Martin, and Mohnen (2017); Worldwide Patent Statistical Database; and IMF staff calculations.

The results suggest that environmental policies have increased the relative share of clean innovation, and even to a larger extent that of gray innovation (Annex Table 3.1.3, column 1 and 2). A possible reason for this is that gray technologies are often less radically new and may thus be closer to the practical application. The effect on overall innovation (column 4) is strong and positive suggesting that the relative decline in dirty innovation (column 3) was more than offset by the increase in the other categories.

Annex Table 3.1.3. Relative and Absolute Electricity

Dependent variables: Patent families related to different types of electricity	(1) Clean	(2) Gray	(3) Dirty	(4) Total
EPS_{t-1}	0.0688***	0.151***	-0.0405**	0.175***
	(0.02)	(0.04)	(0.02)	(0.04)
Log all $tech_{t-1}$	0.0522	-0.338***	0.0543**	0.450***
	(0.10)	(0.10)	(0.02)	(0.07)
Log knowledge stock specific to the type of $electricity_{t-1}$	-0.0255	0.531***	0.0391	
	(0.07)	(0.07)	(0.30)	
Log knowledge stock for all types of $electricity_{t-1}$	-0.00121	0.132	-0.103	0.581***
	(0.17)	(0.21)	(0.30)	(0.10)
Log oil and gas $reserves_{t-1}$	-0.129**	-0.0843	0.0398	
	(0.05)	(0.06)	(0.02)	
Number of observations	738	743	743	781

Source: IMF staff calculations.

Note: Besides the overall EPS indicator, the regression controls for total patenting, the existing knowledge stocks in the specific and overall electricity technology and proven oil and gas reserves. Columns 1 to 3 control for overall electricity innovation with a coefficient constrained at 1. EPS = environmental policy stringency; all tech = total patenting in all technologies.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Conclusion

The evidence suggests that the tightening in environmental policies had a statistically and economically significant effect on clean energy innovation. A closer look at the electricity sector suggests that this resulted in a relative shift away from dirty and towards clean and gray innovation, with a net positive effect on electricity innovation overall.

Annex 3.2. Drivers of the Energy Transition with a Focus on Support Policies and Carbon Pricing

Introduction

The substitution of fossil-fuel power plants with renewable energies such as solar photovoltaic (PV) modules and wind turbines is undoubtedly one of the most important tools countries have at their disposal to mitigate carbon emissions in the electricity sector. From 2001 to 2020 the share of all renewables in nominal global power plant investment increased from 44 percent to 66 percent, with that increase being larger in advanced economies (from 44 to 75 percent) than in developing economies (from 44 to 60 percent) (IEA, 2020b). As the costs of solar PV and onshore wind declined by 82 percent and 63 percent respectively between 2000-2019 (IRENA, 2020), the (real) renewable share in terms of total capacity installed increased even faster.

Main Question & Literature Review

The investment boom in solar, wind and biomass has led to a rapidly increasing share of these renewable energy sources in global power generation, with its share increasing from virtually nil in 2000 to 6.5 percent in 2017, and with much higher shares attained in some EU countries such as Denmark, Germany and the United Kingdom. Furthermore, the pace of this ongoing energy transition is in fact accelerating while the global share increased by about 0.5 percentage point per year in 2010 that number had increased to 1 percentage point in 2017. To understand whether this transition (and its acceleration) can be sustained, it is important to understand its drivers, especially levers for policy makers. To this end we ask: what has been the role of support policies and carbon pricing in driving the energy transition?

According to Bourcet (2020), who reviews a total of 48 papers studying the drivers of renewable energy development, consensus exists in the literature for the following drivers: (i) renewable energy support policies (positive effect), (ii) lobby effect from pre-existing energy sources (negative effect), (iii) (lagged) CO2 emissions per capita (negative effect for the renewable energy share, especially within Europe), (iv) population size (positive effect, as larger countries are expected to contribute more to a global public good), (v) income (positive effect for developing countries).

Only a few studies, i.e., Burke (2010), Best (2017), and IMF (2018), analyze the share of renewable energy/electricity in conjunction with the share of other (polluting) primary energy sources such as coal. Studying the shares of different energy sources simultaneously can provide for a more complete picture of how policies to support renewables and/or reduce carbon emissions have changed the energy/electricity mix.

Empirical Specification

Since a growing renewable energy share is a necessary (but not sufficient) condition to mitigate greenhouse gas emissions from energy use, the annual change in the share of non-hydro renewable energy in electricity generation is selected as our main dependent variable.[7] Other dependent variables analyzed are: the annual change in the shares of coal and natural gas in electricity generation, and total electricity generation per capita (in MWh/capita).

This analysis contributes to the literature by analyzing the effects of various environmental policies on the shares of various primary energy sources in the electricity mix. It does so by regressing the change in the share of renewable electricity on a package of various environmental policy instruments, which limits omitted variable bias potentially affecting single-policy regressions. As the policies are measured as indexes and the underlying units of measurement differ, it should be noted that one cannot directly compare the effect of one policy instrument with another (see below).

To explain the annual change in the share of renewable electricity generation Δy_{it}, we adopt the empirical specification from Urpelainen and Smith (2014). With *i* indexing countries and *t* indexing years, the equation to be estimated reads as follows:

$$\Delta y_{it} = \beta_1 y_{i,t-1}^{MA} + \beta_2 \boldsymbol{Policy_{it}} + \beta_3 X_{it-1} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $y_{i,t-1}^{MA}$ is the three year-moving average of the share of renewable electricity generation lagged by one period, $\boldsymbol{Policy_{it}}$ is a vector of environmental policies and electricity market reforms, X_{it-1} is a vector of controls including income per capita, the interest rate, the electricity share of hydro and nuclear, and proven reserves of natural gas and oil all lagged by one period. To control for unobservable determinants that are country-specific (e.g., citizens' environmental values), and time-specific (e.g., variations in prices of solar and wind that are common to all countries), we include country fixed effects and year fixed effects, denoted by μ_i and λ_t respectively. As in Verdolini and others (2018) we use the OLS panel fixed effects estimator.

Urpelainen and Smith (2014) also employ an instrumental variable approach to deal with the possible reserve causality between the deployment of renewables and feed-in tariffs. If anything, Urpelainen and Smith (2014) find that OLS underestimates the true effect of feed-in tariffs, but in contrast to our work they do not control for other support policies such as renewable energy certificates or carbon pricing. Rodríguez and others (2015) study the relationship between various environmental policies and private sector investment. They find that 2SLS estimates of the effect of feed-in tariffs and renewable energy standards on private sector investment do not differ much from OLS. In their analysis, a Hausman test confirms the exogeneity of these renewable energy policies. While these considerations and others leave little doubt that some policy instruments have had positive effects, it remains prudent to interpret the results from our analysis as associations rather than causal effects.

[7] A growing renewable electricity share is a sufficient condition for reducing emissions if and only if total electricity demand growth is zero (or negative).

Data

Dependent Variables

The following dependent variables are all taken from the IEA (2019) and span the period from 1990 to 2017: (i) the annual change in the share of renewable electricity, (ii) the annual change in the share of electricity from natural gas, (iii) the annual change in the share of electricity from coal, and (iv) the annual change in electricity generation per capita. Renewable electricity includes solar PV, solar thermal, onshore wind, offshore wind, geothermal, wave/tidal/current, and biomass.[8]

Independent Variables

To measure the stringency of environmental policies across countries over time, data from the OECD Environmental Policy Stringency (EPS) project is used (see Botta and Koźluk 2014). The OECD EPS is the only long-run time-series of a comprehensive package of environmental policies in existence. The EPS is measured as an index on a scale from 0 to 6. It includes cross-country comparable data for 32 OECD and emerging market countries between 1990-2015 for various policy indicators including: taxes on the pollutants NOx, SO2 and particular matter (PM); trading schemes for CO2, SO2, renewable (or green) energy certificates, and white certificates (which are tradable assets proving that a certain amount of energy savings has been attained relative to some baseline); feed-in tariffs for solar and wind; limits on emissions of PM, SO2 and NOx for newly built coal-fired power plants, and government R&D expenditures for renewable energy technologies.

Two policy instruments of particular interest are feed-in tariffs and green certificate schemes. Under feed-in tariffs producers of renewable energy are provided with long-term contracts that stipulate a fixed price per kWh for every unit of electricity provided to the grid. Green certificates or renewable energy certificates are tradable assets which prove that electricity has been generated by a renewable energy source. Many states and countries have implemented renewable energy standards, under which utilities are obliged to source a certain fraction of their electricity from renewable sources. If utilities cannot generate the renewable electricity themselves, they must buy green certificates from producers who hold them in excess to prove their compliance.

Other independent variables include: proven reserves for oil and gas from BP (2019) (to control for resource endowments); population size and real income from the Maddison Project Database (Bolt and others 2018) (to proxy for higher demand for environmental quality among others); short-term interest rates from the IMF WEO database (to proxy for the opportunity cost of investment); shares of hydropower and nuclear energy in electricity generation from IEA (2019) (to control for other low-carbon energy sources); electricity market regulation from

[8] Hydropower is not considered because although it is a mature and relatively cheap renewable energy technology, most of the world's reserves are utilized except for a few regions such as the Congo basin. Furthermore, utilization comes with considerable negative environmental effects.

OECD (Koske and others 2015); and the price of oil expressed in local currency units relative to the domestic price level from the IMF primary commodity price tables (IMF, 2020b).

Results

Renewable Energy

Our main results are reported in Annex Table 3.2.1. Model 1 tests the role of market-based and non-market based environmental policies. While positive and statistically significant evidence is found for market-based policies, non-market-based policies do not appear to have been effective. Abstracting from variations in environmental policy stringency and prices of solar and wind energy common to all countries in our sample by incorporating year fixed effects, the average tightening of market-based environmental policies between 1990 and 2010 can explain a 0.38 percentage point increase in the share of renewable electricity generation per year. To put this into perspective, 0.38 percentage points is equivalent to (i) 29 percent of the average model-implied increase in the share of renewable electricity in the last year of our sample, 2014, and (ii) 55 percent of the actual increase of 0.69 percentage points in our sample of 32 countries in that same year.

Model 2 unpacks the role of market-based policies by distinguishing between three types of market-based policy indices: feed-in tariffs, taxes, and trading schemes. The effects of feed-in tariffs and trading schemes are statistically and quantitatively significant. A one standard deviation tightening of these policies increases the share of renewable energy by 0.118 and 0.183 percentage points respectively per annum. For a better appreciation of the potency of feed-in tariffs, consider the case of Germany. Between 1997 and 2007 this European frontrunner in renewable electricity generation scored a 4 or higher on the OECD feed-in tariff variable. Based on Model 2 a country implementing such a policy for a decade would add 2.5 percent to its share of renewable electricity. The cumulative indirect effect of such a feed-in tariff—which works through the increasingly higher share level—would add another 7.5 percent over the same decade.

Model 3 digs further into the role of trading schemes by separating between three types of schemes: CO2 trading schemes, green certificates, and white certificates. Somewhat surprisingly, green certificates are the only type of trading scheme for which statistically significant evidence is found. A one standard deviation change in the green certificates variable, while controlling for all other policies, is found to increase the share of renewable electricity generation by 0.116 percentage points per year, which suggests that the significant evidence for trading schemes from Model 2 is mostly picking up the effect of the green certificates policy indicator. We attribute the lack of statistical evidence for an effect of CO2 trading schemes (e.g., the EU ETS) on renewable electricity generation to two (related) aspects: limited sample variation and the fact that these policies on average have been relatively weak compared to other instruments such as green certificates and feed-in tariffs.

Models 4, 5 and 6 extend Models 1, 2 and 3 respectively with additional controls. By and large, the coefficients on the environmental policy variables are not sensitive to the inclusion of these variables. This suggests that the regression coefficients on environmental policies in the parsimonious models 1-3 are not affected by omitted variables. Statistically significant evidence is found for the role of income (negative effect) and the share of nuclear power in electricity generation (negative effect). These findings are in line with the literature. Previous studies confirmed the negative role of income for OECD countries. Likewise, since nuclear power is a low-carbon technology, countries that are heavily dependent on nuclear energy for electricity generation will have an incentive to invest less in renewable energy.

In all models a statistically significant effect is found for the role of electricity market deregulation. This effect is also quantitatively relevant. The average de-regulation of electricity markets that took place in OECD countries between 1990 and 2010 has supported an annual increase of 0.38 percentage point of the share of renewable electricity generation. Stated otherwise, a one standard deviation increase in the degree of deregulation corresponds to a 0.223 percentage point increase in the share of renewable electricity generation per year.

Electricity Mix and Electricity Generation Per Capita

In part due to their relatively stringent package of environmental policies, several countries including Denmark, Germany and the United Kingdom have become renewable energy frontrunners, with their electricity share of wind, solar and biomass exceeding 30 percent in recent years. This begs the question of whether their policies have merely shifted the electricity mix, or whether they also have affected total electricity generation—for example by raising average electricity prices. To this end we turn to explaining the relationship between environmental policies and the electricity shares of coal and natural gas as well as total electricity generation per capita in Annex Table 3.2.2. As before our dependent variable measures the annual change.

By and large, the results in Annex Table 3.2.2 are in line with our hypotheses: while policy indicators such as feed-in tariffs and CO2 schemes have a positive relationship with the share of solar, wind and biomass in electricity generation, such policies do not appear to have had a discernible impact on total electricity generation. The analysis also shows that the relationship between the EPS variable and fossil fuel electricity shares are not statistically significant at conventional confidence levels, but the sign of the regression coefficients often points in the expected direction. For example, the EPS variables tend to have a negative association with the annual change of the coal share, and the effects on the share of natural gas are ambiguous, perhaps because natural gas plants and their ability to dispatch electricity quickly can complement intermittent renewable energies.

Annex Table 3.2.1. Main Results (1990–2014)

Dependent variable: Δ(electricity share of renewables)	(1)	(2)	(3)	(4)	(5)	(6)
Solar wind and biomass share MA_{t-1}	0.0852**	0.0791*	0.0826*	0.0808*	0.0741+	0.0799+
	(0.0304)	(0.0361)	(0.0365)	(0.0361)	(0.0410)	(0.0419)
Policy variables						
Market EPS	0.231*			0.249*		
	(0.0974)			(0.101)		
Non-market EPS	-0.124	-0.147	-0.146	-0.109	-0.140	-0.138
	(0.106)	(0.113)	(0.113)	(0.122)	(0.131)	(0.130)
Market EPS taxes		0.0842	0.0860		0.132	0.133
		(0.151)	(0.147)		(0.163)	(0.155)
Market EPS feed-in tariff		0.0621*	0.0625*		0.0658*	0.0666*
		(0.0287)	(0.0290)		(0.0305)	(0.0307)
Market EPS trading		0.166**			0.174**	
		(0.0543)			(0.0622)	
Market EPS trading green certificates			0.0918*			0.108**
			(0.0373)			(0.0322)
Market EPS trading CO_2			0.0392			0.0298
			(0.0360)			(0.0388)
Market EPS trading white certificates			0.0561			0.0491
			(0.102)			(0.101)
Log electricity PMR_{t-1}	-0.440**	-0.441**	-0.445**	-0.563**	-0.557**	-0.568**
	(0.159)	(0.149)	(0.141)	(0.197)	(0.184)	(0.174)
Controls						
Log GDP per $capita_{t-1}$	0.0607	0.0320	0.113	-0.951+	-0.996*	-0.898+
Short-term interest $rate_{t-1}$				0.000731	0.00247	0.00176
Log crude oil $price_{t-1}$				-0.511	-0.504	-0.542
Proven oil reserves per $capita_{t-1}$				-72.98+	-41.57	-47.24
Proven natural gas reserves per $capita_{t-1}$				847.8	719.7	890.8
Hydropower $share_{t-1}$				-0.00900	-0.0104	-0.0122
Nuclear $share_{t-1}$				-0.00909	-0.0105	-0.00976
Number of observations	652	652	652	558	558	558
Number of countries	32	32	32	28	28	28
R^2	0.28	0.28	0.28	0.28	0.28	0.28

Source: IMF staff calculations.

Note: Robust standard errors clustered at the country level in parentheses, not reported for controls. Variables are in logarithmic scale. Constant included, but not reported. EPS = Environmental policy stringency; MA = moving average; PMR = product market regulation.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Annex Table 3.2.2. Electricity Mix (1990–2014)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables:	Δ(electricity share of renewables)	Δ(electricity share of renewables)	Δ(electricity share of coal)	Δ(electricity share of coal)	Δ(electricity share of natural gas)	Δ(electricity share of natural gas)	Δ(electricity generation per capita)	Δ(electricity generation per capita)
Solar wind and biomass share MA_{t-1}	0.0826*	0.0799+						
	(0.0365)	(0.0419)						
Coal electricity share MA_{t-1}			-0.0930***	-0.0821**				
			(0.0225)	(0.0293)				
Natural gas electricity share MA_{t-1}					-0.0878***	-0.0972***		
					(0.0172)	(0.0233)		
Electricity generation per capita MA_{t-1}							-0.281+	-0.319+
							(0.164)	(0.166)
Policy variables								
Market EPS taxes	0.0860	0.133	-0.0885	-0.0771	-0.298	-0.237	0.0407	0.0358
	(0.147)	(0.155)	(0.194)	(0.260)	(0.226)	(0.284)	(0.107)	(0.105)
Market EPS feed-in tariff	0.0625*	0.0666*	-0.0574	-0.0532	0.106	0.130	-0.00233	-0.00160
	(0.0290)	(0.0307)	(0.0764)	(0.0821)	(0.0940)	(0.108)	(0.0139)	(0.0138)
Market EPS trading green certificates	0.0918*	0.108**	0.00752	-0.0500	0.00692	-0.0101	-0.00158	-0.00843
	(0.0373)	(0.0322)	(0.0915)	(0.0838)	(0.119)	(0.135)	(0.0233)	(0.0228)
Market EPS trading CO_2	0.0392	0.0298	-0.153	-0.0391	-0.0560	-0.0214	-0.0297	-0.0411
	(0.0360)	(0.0388)	(0.0989)	(0.0911)	(0.0684)	(0.0698)	(0.0237)	(0.0264)
Market EPS trading white certificates	0.0561	0.0491	0.238	0.233	-0.376	-0.414	-0.0586	-0.0607
	(0.102)	(0.101)	(0.221)	(0.226)	(0.274)	(0.328)	(0.0367)	(0.0430)
Non-market EPS	-0.146	-0.138	-0.330	-0.350	0.173	0.321	0.0335	0.0671
	(0.113)	(0.130)	(0.195)	(0.234)	(0.213)	(0.221)	(0.0672)	(0.0854)
Log electricity PMR_{t-1}	-0.445**	-0.568**	0.389	0.503	0.617	0.117	0.0188	0.0114
	(0.141)	(0.174)	(0.359)	(0.530)	(0.633)	(0.735)	(0.0974)	(0.122)
Controls								
Log GDP per $capita_{t-1}$	0.113	-0.898+	0.518	2.106	2.545*	-0.325	0.423*	0.687
Short-term interest $rate_{t-1}$		0.00176		0.106*		-0.0969*		-0.0228+
Log crude oil $price_{t-1}$		-0.542		1.388*		-0.162		0.140
Proven oil reserves per $capita_{t-1}$		-47.24		-17.14		-92.29		-100.2
Proven natural gas reserves per $capita_{t-1}$		890.8		-6299.6		5473.0		388.5
Hydropower $share_{t-1}$		-0.0122		0.198**		0.143*		
Nuclear $share_{t-1}$		-0.00976		0.00656		-0.0256		
Number of observations	652	558	652	558	652	558	652	558
Number of countries	32	28	32	28	32	28	32	28
R^2	0.28	0.28	0.10	0.17	0.20	0.25	0.10	0.11

Source: IMF staff calculations.

Note: Robust standard errors clustered at the country level in parentheses, not reported for controls. Constant included, but not reported. EPS = Environmental policy stringency; MA = moving average; PMR = product market regulation.

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1.

Annex 3.3. Employment Effects of Environmental and Green Supply Policies

Environmental Policies and Labor Demand at the Firm Level

Introduction

The impact of environmental policies on employment has become an important issue particularly in view of the growing call for a "green" recovery, amid widespread labor market stresses due to the pandemic. While there is relatively wide support for the view that renewable energy and energy efficiency can be more job-intensive than fossil fuels,[9] there is more ambiguity about the impact of other environmental policies, for instance regarding the impact of carbon taxation.[10] For example, using sectoral data, Yamazaki (2017) finds that carbon taxation implemented in the British Columbia province of Canada led to a fall in employment in carbon-intensive and trade-intensive sectors, offset by an increase in employment in low-carbon service industries, yielding a small overall positive effect. Examining the same policy change but using household data, Yip (2018) comes to the opposite conclusion: carbon taxation resulted in a small increase in the unemployment rate, with the effects concentrated on low- and medium- skilled workers. Using a sample of EU countries Stock and Metcalf (2020) do not find evidence of significant negative employment effects in aggregate data; indeed, their results also suggest a modest positive impact. Relatively few papers appear to look at labor demand in micro data; one example is Kahn (1997) who examines the effect of particulate matter regulation in the United States and finds that employment growth was weaker in plants located in "non-attainment" areas (i.e., areas that did not meet the national air quality standard) in certain sectors. Similarly, Greenstone (2002) found that in a large sample of U.S. plants, carbon monoxide and ozone regulations had strong depressing effects on labor demand in non-attainment counties, especially among industries that emitted multiple pollutants (e.g., pulp and paper, and petroleum refining industries). Finally, Liu and others (2017) use plant-level data from China to show that firms impacted by more stringent waste-water regulations in the Jiangsu region of China reduced their labor demand quite significantly.

Estimation Methodology

The basic approach is to estimate an augmented labor demand equation, controlling for standard determinants in the literature (e.g., Van Reenen 1997), and introducing the EPS indicator, interacted with an indicator variable to capture the intensity of a firm's CO2 emissions. The estimating equation is

$$n_{i,t} = \sum_{k=1}^{T} a_k\, n_{i,t-k} + \boldsymbol{bX}_{i,j,t} + c_1[EPS_{j,t} \text{ x } d_C] + d_C + d_i + d_j + d_t + \varepsilon_{i,t}; \text{ where}$$

$$d_C = 1\ if\ CO2\ emissions = \text{"high"},\ \ 0\ otherwise$$

[9] See Wei, Patadia, and Kammen (2010) for evidence on the U.S., and Stavropoulos and Burger (2020) for an extensive review of the literature. IEA (2020a) looks at the global job-creation potential of a green investment push as part of an economic recovery plan in the wake of the pandemic.

[10] See Deschenes (2018) for a brief and useful summary of research on environmental regulation and employment.

All variables are expressed in logs, except the EPS indicator which enters in levels. Firm-level employment $n_{i,t}$ is regressed on its own lags, a vector of controls, and firm i, country j, and year t fixed effects. The vector of controls $\boldsymbol{X}_{i,j,t}$ includes firm-level average annual employee wages; real capital stock (sum of building and machinery capital stock deflated by the building and machinery price indices from Penn World Tables); the rental rate of capital (proxied by the price of capital services, taken from Penn World Tables); and the output gap.[11] $EPS_{j,t}$ x d_C is the interaction of interest, where EPS refers to the value of the selected environmental policy indicator in country j and time t. This specification is referred to below as Specification 1.

In an alternative Specification 2, the CO2 emission intensity is proxied by the sector of the firm in order to expand coverage of the sample, given the relatively low count of firms reporting actual CO2 emissions. In the interaction term, the CO2 emission dummy is replaced with a sector dummy. Following Van Reenen (1997), the estimation methodology is panel GMM.

Data

The firm-level data are from the Worldscope database. From the original Worldscope sample of more than 30,000 firms, only firms reporting unbroken spells of data on employment, staff costs, and capital stock are selected. For the specification interacting EPS with the CO2 emissions indicator, an additional restriction for inclusion in the sample is imposed, namely that the firm must report at least 3 instances of CO2 emissions. For each firm, only the longest spell including all the required variables is selected.[12] The

Annex Table 3.3.1. Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Sample 1: Interaction with high/low CO_2				
Aggregate EPS	2.5	0.9	0.4	4.1
Market EPS	1.9	1.0	0.0	4.0
EPS: CO_2 tax	0.1	0.9	0.0	6.0
Non-market EPS	3.1	1.2	0.6	5.5
Log employees	9.6	1.5	2.8	13.4
Log capital stock	14.5	1.8	8.3	19.6
Log wage	3.9	0.8	-3.4	11.5
Log r	0.0	0.1	-0.8	0.6
Output gap	0.0	2.2	-15.4	8.9
Log CO_2 emissions	8.9	10.0	-1.3	12.3
Sample 2: Interaction with sector dummies				
Aggregate EPS	2.2	0.9	0.4	4.1
Market EPS	1.7	0.9	0.0	4.0
EPS: CO_2 tax	0.1	0.8	0.0	6.0
Non-market EPS	2.7	1.3	0.6	5.5
Log employees	7.8	1.9	0.0	13.4
Log capital stock	12.2	2.2	3.4	19.5
Log wage	3.2	1.2	-3.8	11.5
Log r	0.0	0.1	-0.8	0.6
Output gap	-0.2	2.0	-15.4	8.9

Source: IMF staff calculations.

Note: Estimation sample 1 includes 670 firms, from 30 countries over 2000–15. Sample 2 consists of 5,305 firms, covering 31 countries over 2000–15. Capital stock is calculated as sum of machinery and building stock (in thousand US dollars), deflated by corresponding capital goods price deflators from Penn World Tables. Wages are calculated as total staff costs (in thousand US dollars) divided by total employees. Rental rate r is log of the price of capital services at the country level, from Penn World Tables. CO_2 emissions are measured in thousand tons. EPS = environmental policy stringency.

[11] Assuming a standard CES production function, Van Reenen (1997) derives labor demand as a function of real output and real wage, or, substituting for real output with capital, as a function of nominal factor prices and the real capital stock. The specifications implemented here follow the latter approach. However, we note that the results are robust to substituting nominal wages with real wages (defined as the nominal wage deflated by the aggregate CPI price index). Note also that all firms in a country are assumed to have the same rental rate of capital which is a simplifying assumption. This is similar to Van Reenen (1997) who proxies the rental rate with year fixed effects for a panel of UK firms.

[12] Few firms report unbroken spells of CO2 emissions. To make use of the available information in the best possible manner, a firm is coded as high-emission if its emissions-to-employees ratio exceeds the median for the country-year in any year that it reports this data. Thus, this is a time-invariant property of the firm in this framework. On average, a high-emission intensity firm emits more than 10 times more CO2 than a low-emission intensity firm. The relatively sparse reporting on CO2 emissions raises questions about selection issues if reporting emissions is an

samples consist of 670 firms when the availability of CO2 emissions data is taken into account; and 5305 firms when using sectoral dummies instead. The data span 31 countries over 2000-2015. Additionally, data on rental rate of capital is taken from Penn World Tables (using the price of capital services index as a proxy). The EPS variables are from OECD, measured as indices on a scale from 0 to 6. These include cross-country data for 32 OECD and emerging market countries between 1990-2015 for various policy indicators, including aggregate, market-based, and non-market-based policies, and sub-indices that further disaggregate these policies for instance into tax, trading, regulatory limits, subsidies, etc. Finally, controls for the output gap are from the IMF *WEO* database. Annex Table 3.3.1 presents summary statistics of the variables for the two samples used.

Results

Annex Table 3.3.2 shows the results of Specification 1. Column 1 shows the results of a standard labor demand equation, incorporating 2 lags of employment, and controlling for wages, rental rate of capital, and capital stock. The coefficient estimates of the standard determinants of labor demand are all highly statistically significant and have the expected sign with respect to factor prices, capital stock, as well as lags of employment. In column 2, the interaction term of aggregate EPS with the CO2 emissions dummy is included. The interaction is significant, indicating that high-emission firms experience negative employment effects in response to tightening EPS, whereas low-emission firms experience an increase in employment (although the effect is not significant for low-emission firms). The estimated semi-elasticities suggest that a 1-standard deviation tightening in the EPS indicator would lower employment in high-carbon firms by 5 percent, but raise employment in low-carbon firms by 2.6 percent. Column 3 shows the results for market EPS. The coefficients again suggest that employment would decline in high emission-intensity firms and increase in low emission-intensity ones. The results are qualitatively similar for carbon taxation (though again not significant; column 4). In the case of non-market EPS (column 5), the coefficients on both non-market EPS and its interaction with the emission intensity indicator are significant, suggesting that a 1-standard deviation tightening in the non-market EPS would lower employment in high-emission firms by 5 percent, and raise it in low-emission firms by 4.4 percent. [13]

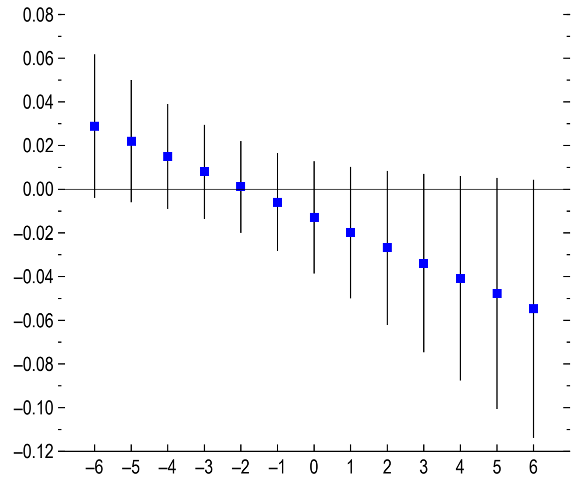
endogenous choice by firms. It is possible that high-emission firms do not report CO2 emissions to avoid market consequences, for instance. Looking across sectors, however, a higher proportion of firms in high-emission sectors—fossil fuel industries (26%), transport industries (24%), and utilities (34%)—report at least one year of CO2 emissions relative to the average rate of at least one CO2 emission report across all firms in all the sectors (21%). The exception is high-emission manufacturing (15%). This pattern is also observed when considering firms that report at least 3 instances of CO2 emissions (a condition imposed to be included in the regression sample). Across countries, the share of firms reporting at least on year of CO2 emissions in China, India and Indonesia is relatively much lower than in other OECD countries (3%, 4%, and 5% respectively of sample firms compared to the sample average of 32%). However, the frequency of "high-emission" firms from these countries (among the firms that do report emissions), is very similar to the sample average. These factors would suggest that a selection bias is unlikely to be present in this case.

[13] These results are robust to setting the high/low emission intensity threshold at a different level, for example at the 75th percentile of the distribution within a country-year, in place of the median. The results are also broadly robust to excluding all firms with fiscal year ending before December of the given year in terms of the sign of the coefficients, but they lose statistical significance as the sample size is significantly reduced. Results available upon request.

To examine the sensitivity of the employment-EPS relationship to cyclical conditions, in columns 6 through 9, we also include an interaction of the output gap with the EPS indicator. The output gap term has the expected sign, though it is only significant in the regression considering market EPS. Column 7 also shows that the market EPS indicator can have a positive employment effect when the output gap is negative. Indeed, the average marginal effects of market EPS on employment are modestly positive under severe contractionary conditions, and turn negative during normal/expansionary periods (see also Annex Figure 3.3.1). An explanation for this pattern may lie in the inflationary impact of tighter EPS, which under severe contractionary conditions may help to lower the real rate of interest (for instance if policy rates are at the zero-lower bound), thus stimulating demand.[14]

Annex Figure 3.3.1. Impact of Market EPS on Employment Conditional on Output Gap

(Effects on fitted values on y-axis, output gap percent of potential on x-axis)



Sources: Worldscope database; and IMF staff calculations.
Note: Figure shows point estimates and 95 percent confidence intervals. EPS = environmental policy stringency.

Turning to Specification 2, Annex Table 3.3.3 provides additional detail on the sectoral classification and sample characteristics. This specification helps to increase the sample size substantially. There are more firms in the sample from among low-emission industries, services, and high-emission industries, and fewer firms from the other sectors, with the utilities sector having the fewest. However, it does not appear that there are too few firms in any one sector.

Annex Table 3.3.4 shows results from replacing the CO2 emission dummy in Specification 1 with sector dummies to proxy for emission intensity. The interactions span the entire sample of firms included in the regressions. Six sectors are included in the baseline: fossil fuel industries, high-emission manufacturing industries (food, metals and minerals, chemicals, paper and packaging)[15], services, construction, transport, and other (low-emission) manufacturing industries.

Column 2 shows the results for aggregate EPS. Each of the interactions has the expected sign (individually significant in the case of construction industries), and the set of interactions are jointly significant. The construction sector here includes not only residential but also commercial and industrial construction. The sector uses high-emission inputs such as cement, and thus the negative effect from tighter EPS may reflect both the impact on the cost of high-emission inputs, and a negative effect due to lower activity in high-emission sectors. For market EPS

[14] Evidence for expansionary effects of negative supply shocks that are otherwise thought to be output-reducing can be found in Eggertsson (2012). For evidence that disputes such negative effects, see Garin and others (2019), and Weiland (2019).

[15] These are among the most emission-intensive industries in Europe for example (see "Sectoral Policies for Climate Change Mitigation in the EU", IMF 2020c. Oil refineries which are also a high-emission industry are included among fossil fuel industries.

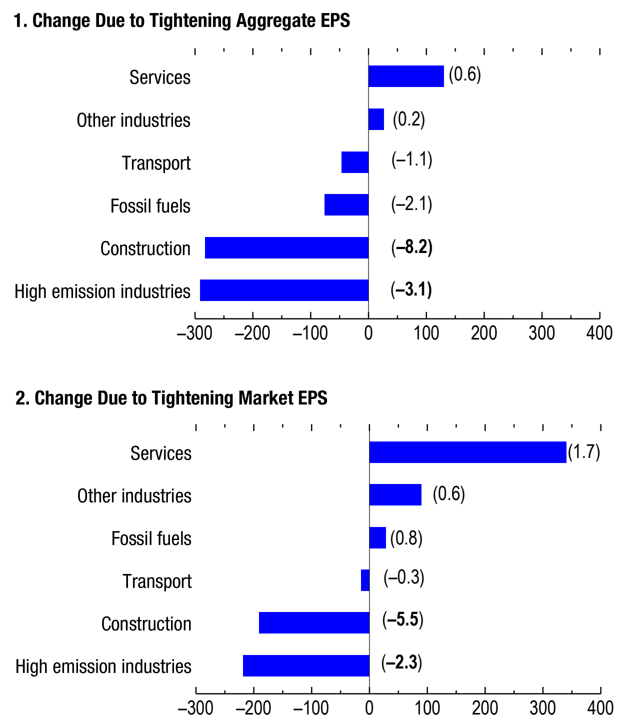
(column 3), the positive impact on services is also statistically significant at the 10 percent level. However, the sign on fossil fuel industries is positive.[16] In the case of non-market EPS, the pattern is similar to that of market EPS, except that the interaction with the fossil fuel sector is negative (column 5).

In columns 6 and 7, the output gap is included as an additional regressor, to capture country-specific macroeconomic conditions. The sign on the output gap is positive and significant, as expected. Upon introducing this control, the coefficient on high-emission manufacturing industries also becomes significant (and remains negative).[17]

These specifications exclude the fossil fuel utilities sector, although it is likely to be significantly impacted by EPS, given the very small number of fossil fuel utilities in the sample. However, a broader utility category is included in a robustness exercise that includes not just fossil fuel utilities, but also multiline utilities whose activities include electricity generation, and also distribution. These regressions are shown in the columns 9 and 10. The sign on the utility's coefficient is negative, as expected, and the interactions remain jointly significant at the 10 percent level.[18]

Based on the preferred specifications that include controls for the output gap, we can also calculate the net impact on total employment in the sample. Based on the estimates in columns 6 and column 9, there is a net loss of between 500-600 thousand jobs (about 1 percent of the total employment in the sample) in the case of aggregate EPS tightening by 1 standard deviation. In contrast, tightening market EPS by 1 standard deviation results in a small net job

Annex Figure 3.3.2. Job Reallocation Effects of Tightening EPS
(Change in employees, thousands)



Sources: Penn World Tables; Worldscope database; and IMF staff calculations.
Note: Bars show change in employment in thousands, and the figures in parentheses are semi-elasticities computed from the interaction between the sector dummy and the EPS indicator, for a one standard deviation tightening of the EPS indicator. For both Aggregate EPS and Market EPS, the interactions are jointly significant at 10 percent (bold numbers in parentheses are semi-elasticities significant at conventional levels). EPS = environmental policy stringency.

[16] The aggregate market EPS reflects the combined effect of different types of market-based policies. Examining the sub-components of market EPS reveals that the interaction with fossil fuels is negative in the case of tax policies, but positive in the case of trading schemes. This likely reflects that trading policies allow firms to maintain output (and employment) by being able to buy pollution permits, whereas increased stringency of tax policies may cause firms to reduce output including by outsourcing polluting activities, or shifting the location of pollutive activities production to jurisdictions with weaker enforcement (see Ben-David and others, 2020, for evidence of multinational firms shifting emissions to other locations). Even for the high-emission industries sector, for instance, although the effect of more stringent trading policies is negative, the effect is insignificant and much smaller than the effect of more stringent tax policy.

[17] The t-statistic rises from 1.2 in the regression excluding the output gap (Column 1), to 1.9.

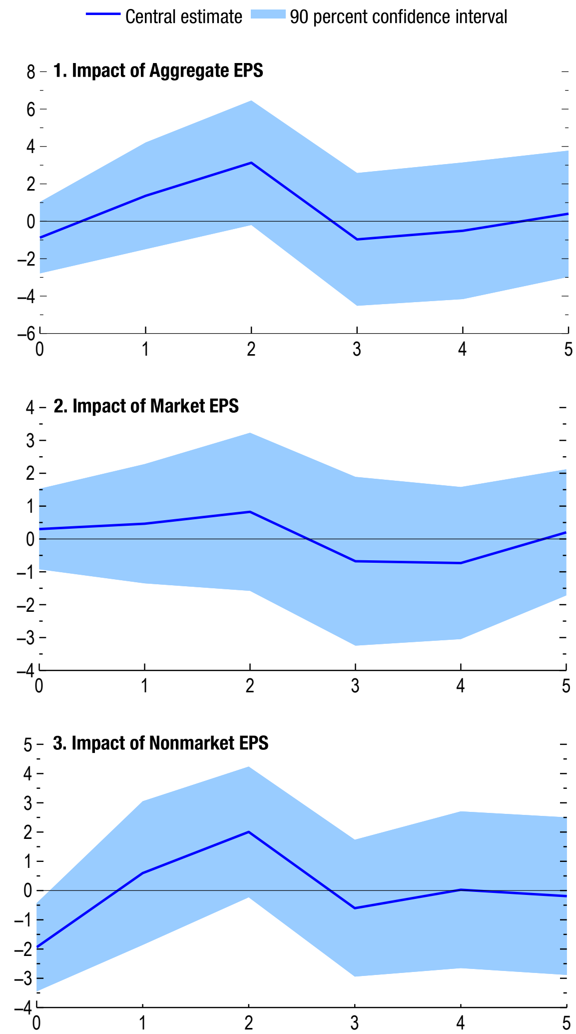
[18] The results are also broadly robust to excluding all firms with fiscal year ending before December of the year. Results available upon request.

increase between 13-34 thousand jobs, based on the estimates in columns 7 and 10 (Annex Figure 3.3.2).

Finally, we implement a set of regressions to examine the medium-term effects of EPS, embedding an estimating equation similar to the specifications above, except that they exclude interactions with CO2 emissions.[19] Thus, we are looking at the average effect over time across all firms from a given change in EPS. Over the medium-term, the short-term effects of aggregate EPS, market EPS, and non-market EPS tend to reverse and fade away (Annex Figure 3.3.3).

Annex Figure 3.3.3. Medium Term Effects of EPS on Jobs

(Percent change; years on x-axis)



Sources: Penn World Tables; Worldscope database; and IMF staff calculations.
Note: Each panel shows the estimated percent change in employment with respect to a unit change in the EPS indicator, and the 90 percent confidence interval, over a five-year horizon. The estimation sample includes 2,148 firms that have at least 10 continuous years of data. The estimation is via local projection using a GMM estimator. The regression includes the level of the EPS variable, and (logs of) two lags of employment, capital stock, factor prices; as well as firm, country, and year fixed effects. EPS = environmental policy stringency.

Conclusions

Based on this exercise, we are able to conclude that at least in the short term, tightening of environmental policies is associated with a reallocation of jobs, with employment rising in low-CO2 emissions firms, and falling in high-CO2 emissions firms. When emissions are proxied by the sector of the firm, the effects suggest a reallocation of labor from high carbon-intensive sectors to low carbon-intensive ones in general. While the evidence generally supports reallocation effects, the overall impact remains somewhat uncertain as it depends on the particular set of policies. Past policy changes suggest that short-term effects are negative with respect to overall EPS, likely driven by negative effects of non-market policies. However, to the extent that future policy changes will rely more on market-based policies, the overall effects may be positive going by these findings. In the case of the carbon taxation, however, it is unclear from the wider literature what the overall effects would be. Regardless, the short-term effects whether net positive or net negative appear to be quite modest. Moreover, the effects tend to fade away over the medium term. Finally, the evidence also suggests that the impact of tightening market-based policies depends on the state

[19] Results available upon request.

of the business cycle. Under highly contractionary conditions, the impact may be positive (other things equal), whereas under more normal or expansionary periods, the effect is negative.

Annex Table 3.3.2. Regression Results (Specification 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EPS Indicator:		Agg EPS	Mkt EPS	CO_2 Tax	Non-Mkt	Agg EPS	Mkt EPS	CO2 Tax	Non-Mkt
Dependent variable:	Log N	Log N	Log N	Log N	Log N	Log N	Log N	Log N	Log N
Log N_{t-1}	0.573***	0.560***	0.566***	0.565***	0.555***	0.556***	0.561***	0.562***	0.552***
Log N_{t-2}	-0.142***	-0.144***	-0.144***	-0.143***	-0.144***	-0.141***	-0.142***	-0.141***	-0.140***
Log capital stock	0.276**	0.266**	0.268**	0.275**	0.263**	0.266**	0.272**	0.273**	0.262**
Log wages	-0.260**	-0.252**	-0.252**	-0.254**	-0.238*	-0.256**	-0.255**	-0.259**	-0.256**
Log r	0.308**	0.292***	0.301**	0.308**	0.300***	0.256**	0.275**	0.284**	0.247**
EPS		0.0270	0.0224	0.0408	0.0355*	0.0243	0.0194	0.0364	0.0282
EPS × (High CO_2 = 1)		-0.0785*	-0.0561	-0.0948	-0.0760**	-0.0799*	-0.0560	-0.0981	-0.0773**
Output gap						0.0151	0.0147**	0.00367	0.0128
Output gap × EPS						-0.00489	-0.00697**	-0.00995	-0.00286
Observations	6,899	5,991	5,991	5,991	5,991	5,991	5,991	5,991	5,991
Number of firms	773	670	670	670	670	670	670	670	670

Source: IMF staff calculations.

Note: "EPS" in the list of explanatory variables refers to Aggregate EPS in column 2 and 6; Market EPS in column 3 and 7; Carbon taxes in column 4 and 8; and Non-market EPS in column 5 and 9. All regressions include panel and year fixed effects. In columns 2-9, wages, capital, and rental rate are GMM-instrumented with lags. The Hansen J-test cannot reject instrument validity at 1% in column 1, at 10% in columns 2-9. EPS = environmental policy stringency; N = employment.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex Table 3.3.3. Descriptive Statistics of Firms by Sector

	Labor			Capital stock			Number
Sector	Median	LQR	UQR	Median	LQR	UQR	of firms
Fossil fuel industries	2,740	763	12,032	544	76	3,369	122
High emission industries	2,299	974	5,907	272	102	848	779
Other industries	2,193	976	5,570	131	50	330	1,160
Services	1,972	811	5,368	98	32	306	955
Construction	2,040	808	6,453	75	38	341	124
Transport	4,500	1,541	12,299	292	77	945	147
Utilities	6,111	1,442	10,944	2,444	1,334	6,072	47

Source: IMF staff calculations.

Note: Labor and capital stock figures are for 2015. Labor is measured in total number of employees, and real capital stock in million US dollars, calculated as deflated sum of building and machinery stock, using appropriate price deflators from Penn World Tables. Sector details: (a) Fossil fuel industries include coal, and oil and gas production, and equipment and services; (b) High emission manufacturing includes metals and mining (excluding fossil fuel mining), construction materials, paper and forest products, containers and packaging, and food and beverages; (c) Other industries include manufacturing industries not in (b); (d) Services include industrial, commercial (professional and business support), consumer services, finance, insurance, real-estate, healthcare, and technology; (e) Construction includes residential, commercial, and industrial/engineering construction; (f) Transport includes freight and passenger transport by land, sea, and air; and (g) Utilities includes fossil-fuel based and multiline utilities. LQR = lower quartile; UQR = upper quartile.

Annex Table 3.3.4. Regression Results (Specification 2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EPS Indicator:		Agg EPS	Mkt EPS	CO2 Tax	Non-Mkt EPS	Agg EPS	Mkt EPS	Non-Mkt EPS	Agg EPS	Mkt EPS
Dependent variable:	Log N	Log N	Log N	Log N	Log N	Log N	Log N	Log N	Log N	Log N
Log N_{t-1}	0.543***	0.555***	0.550***	0.541***	0.551***	0.554***	0.545***	0.549***	0.554***	0.546***
Log N_{t-2}	0.0189	0.0148	0.0157	0.0171	0.0154	0.0157	0.0172	0.0170	0.0172	0.0184
Log capital stock	0.186***	0.189***	0.190***	0.203***	0.191***	0.178***	0.178***	0.179***	0.171***	0.171***
Log wages	-0.218***	-0.218***	-0.216***	-0.226***	-0.218***	-0.215***	-0.214***	-0.218***	-0.214***	-0.213***
Log r	0.241***	0.234***	0.234***	0.242***	0.224***	0.150***	0.148***	0.134***	0.141***	0.139***
Output gap						0.00806***	0.00920***	0.00838***	0.00857***	0.00967***
Fossil fuels × EPS		-0.0181	0.00821	-0.723	-0.0345	-0.0234	0.00980	-0.0380	-0.0243	0.0104
High CO_2 industries × EPS		-0.0228	-0.0257	-0.00432	-0.0212	-0.0346*	-0.0295*	-0.0293**	-0.0361*	-0.0292*
Other industries × EPS		0.0155	0.0131	-0.00534	0.00565	0.00189	0.00726	-0.00436	0.000557	0.00673
Services × EPS		0.0174	0.0225*	-0.00792	0.00517	0.00697	0.0208	-0.00344	0.00545	0.0201
Construction × EPS		-0.0836***	-0.0693**	-0.140	-0.0717***	-0.0906***	-0.0695**	-0.0766***	-0.0919***	-0.0706**
Transport × EPS		-0.00319	-0.00696	-0.0188	-0.00631	-0.0118	-0.00417	-0.0148	-0.0115	-0.000983
Utilities × EPS									-0.0226	-0.0266
Joint significant (p-value)		0.05	0.06	0.65	0.05	0.05	0.07	0.03	0.07	0.10
Observations	28,122	25,631	25,631	25,637	25,637	25,631	25,631	25,631	26,072	26,072
Number of firms	5,579	5,305	5,305	5,305	5,305	5,305	5,305	5,305	5,384	5,384

Source: IMF staff calculations.

Note: "EPS" in the list of explanatory variables refers to Aggregate EPS in column 2; Market EPS in column 3; Carbon taxes in column 4; and Non-market EPS in column 5 and 8; Aggregate EPS in column 6 and 9; and Market EPS in column 7 and 10. All regressions include panel and year fixed effects. Wages, capital, and rental rate are GMM-instrumented with lags. EPS = environmental policy stringency; N = employment.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Annex 3.4. G-Cubed Simulations

The model used for this project follows the approach in the G-Cubed model (McKibbin and Wilcoxen 1999, 2013). A number of changes were implemented specifically for this project compared to the most recent published model in Liu and others (2020). The key changes to the model for this project are:

- The database was significantly updated to include data from GTAP10 and the latest data from the IMF, the World Bank, OECD, UN, and US Energy Information Administration.
- The gas extraction and gas utilities sectors were merged into one gas sector.
- A new sector for construction was added to the model.
- A capacity for implementing government infrastructure investment following Calderon and others (2015) was implemented. Green infrastructure projects were incorporated.

Regions and Sectors

There are 10 regions and 20 sectors in the version of the model (version GGG20v154) used in this report.

Annex Table 3.4.1. Regions in the G-Cubed Model

Region code	Region description
AUS	Australia
CHN	China
EUW	Europe
IND	India
JPN	Japan
OPC	Selected oil-exporting countries and other economies
OEC	Rest of the OECD
ROW	Rest of the world
RUS	Russian Federation
USA	United States

The coverage of each region in the above table is presented below:

- Europe: Germany, France, Italy, Spain, Netherlands, Belgium, Bulgaria, Croatia, Czech Republic, Estonia, Cyprus, Lithuania, Latvia, Hungary, Malta, Poland, Romania, Slovenia, Slovakia, Luxemburg, Ireland, Greece, Austria, Portugal, Finland, United Kingdom, Norway, Sweden, Switzerland, Denmark
- Rest of OECD: Canada, New Zealand, Iceland, and Liechtenstein. For presentational purposes, Australia is included in OEC in the chapter's figures.
- Selected Oil-Exporting Countries and Other Economies: Ecuador, Nigeria, Angola, Congo, Iran, Venezuela, Algeria, Libya, Bahrain, Iraq, Israel, Jordan, Kuwait,

Lebanon, West Bank and Gaza, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, Yemen

- Rest of World: All countries not included in other groups.

The sectors in the model are set out in table 3.4.2.

Annex Table 3.4.2. Sectors in the G-Cubed Model

Number	Sector name	Notes
1	Electricity delivery	Energy sectors other than generation
2	Gas extraction and utilities	
3	Petroleum refining	
4	Coal mining	
5	Crude oil extraction	
6	Construction	Goods and services
7	Other mining	
8	Agriculture and forestry	
9	Durable goods	
10	Nondurable goods	
11	Transportation	
12	Services	
13	Coal generation	Electricity generation sectors
14	Natural gas generation	
15	Petroleum generation	
16	Nuclear generation	
17	Wind generation	
18	Solar generation	
19	Hydroelectric generation	
20	Other generation	

The G-Cubed sectors 1-12 are aggregated from 65 sectors of GTAP 10. We then further disaggregate the electricity sector into the electricity delivery sector (sector 1) and 8 electricity generation sectors (sectors 13-20).

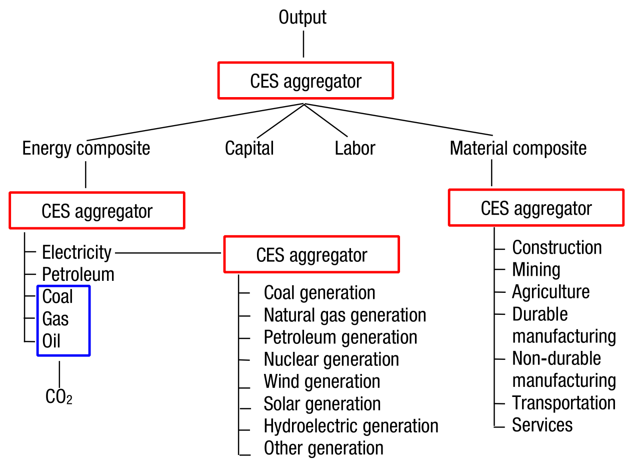
Model Structures and Features

The structure in the model is set out in McKibbin and Wilcoxen (2009, 2013). An illustration of the production structure is contained in Annex Figure 3.4.1. CO2 emissions are measured through the burning of fossil fuels in energy generation.

Several key features of the standard G-Cubed model are worth highlighting here.

- The model completely accounts for stocks and flows of physical and financial assets. For example, budget deficits accumulate into government debt, and current account deficits accumulate into foreign debt. The model imposes an intertemporal budget constraint on all households, firms, government, and countries. Thus, a long-run stock equilibrium obtains through the adjustment of asset prices, such as the interest rate for government fiscal positions or real exchange rates for the balance of payments. However, the adjustment towards the long-run equilibrium of each economy can be slow, occurring over much of a century.

Annex Figure 3.4.1. Production Structure in the G-Cubed Model



Source: McKibbin and Wilcoxen (1999, 2013).

- Agents in G-Cubed must use money issued by central banks for all transactions. Thus, central banks in the model set short term nominal interest rates to target macroeconomic outcomes (such as inflation, unemployment, exchange rates, etc.) based on Henderson-McKibbin-Taylor monetary rules. These rules approximate actual monetary regimes in each country or region in the model. These monetary rules tie down the long-run inflation rates in each country as well as allowing short term adjustment of policy to smooth fluctuations in the real economy.

- Nominal wages are sticky and adjust over time based on country-specific labor contracting assumptions. Firms hire labor in each sector up to the point that the marginal product of labor equals the real wage defined in terms of the output price level of that sector. Any excess labor enters the unemployed pool of workers. Unemployment or the presence of excess demand for labor causes the nominal wage to adjust to clear the labor market in the long run. In the short-run unemployment can arise due to structural supply shocks or changes in aggregate demand in the economy.

- Rigidities prevent the economy from moving quickly from one equilibrium to another. These rigidities include nominal stickiness caused by wage rigidities, lack of complete foresight in the formation of expectations, cost of adjustment in investment by firms with physical capital being sector-specific in the short run, monetary and fiscal authorities following particular monetary and fiscal rules. Short term adjustment to economic shocks can be very different from the long-run equilibrium outcomes. The focus on short-run rigidities is important for assessing the impact over the initial decades of demographic change.

- The model incorporates heterogeneous households and firms. Firms are modelled separately within each sector. There is a mixture of two types of consumers and two types of firms within each sector, within each country: one group bases their decisions on forward-looking expectations and the other group follows simpler rules of thumb which are optimal in the long run, but not necessarily in the short run.

- The fiscal rule in the model varies across model versions. In the version of the model in this report we assumed an exogeneous budget deficit (it changes according to the revenue generated by carbon taxes or lost through various subsidies or changes in infrastructure spending) with lump sum taxes on households adjusted to ensure fiscal sustainability. In the long run the changes in interest servicing costs from any changes in revenue or expenditure that is exogenously imposed is offset through a lump sum tax on households. Thus, the level of government debt can permanently change in the long run with the change in the debt-to-GDP ratio equal to the ratio of the long run fiscal deficit to the long run real growth rate of the economy.

Baseline Inputs and Assumptions

The key inputs into the baseline are the initial dynamics from 2018 to 2019 and subsequent projections from 2019 onwards for sectoral productivity growth rates by sector and by country. Sectoral productivity growth is driven by labor force growth and labor productivity growth.

- Labor force: We use the working-age population projections from the UN Population Prospects 2019 to calculate our economy-wide labor growth rates.

- Labor productivity: We use a catch-up model to generate labor productivity growth rates (labor-augmenting technological progress). The sectoral productivity projections follow the Barro approach estimating that the average catchup rate of individual countries to the worldwide productivity frontier is 2% per year. We use the Groningen Growth and Development database to estimate the initial productivity level in each sector of each region in the model, and then take the ratio of the initial productivity to the equivalent sector in the US (the frontier). Given this initial gap, we use the Barro catchup model to generate long-term projections of the productivity growth rate of each sector within each country. Where we expect that regions will catch up more quickly to the frontier due to economic reforms or more slowly to the frontier due to institutional rigidities, we vary the catchup rate over time. The calibration of the catchup rate attempts to replicate recent growth experiences of each country and region in the model.

Scenarios

Carbon tax

Net Zero Emissions in 2050

In the G-Cubed model, there are fossil fuels and renewable sectors, but no carbon removal technologies. To achieve net zero emissions by 2050 in the real world, carbon removal technologies also play an important role. IPCC (2018b) provides a review on carbon removal technologies, of which one main reference is Fuss (2018).

We draw on the estimates of carbon removal potentials from Fuss (2018). The estimates of global carbon removal technologies by 2050 by Fuss (2018) are as follows:

Annex Table 3.4.3. Global Carbon Removal Potentials in 2050

(Gigaton CO_2)

Carbon removal technologies	Potentials
Afforestation and reforestation	0.5–3.6
BECCS	0.5–5
Biochar	0.5–2
Enhanced weathering	2–4
DACCS	0.5–5
Soil carbon sequestration	Up to 5

We take the average of the range for each technology and sum them up (13.8Gt CO2). We make a conservative assumption that about 75% of 13.8 Gt can be achieved by 2050, i.e., about 10Gt CO2 per year. This is about 20% of global CO2 emissions in the baseline in 2050. We assume that all regions in our model reduce their emissions by 80% by 2050 relative to 2018 except OPC remains at the same level of 2018 by 2050.

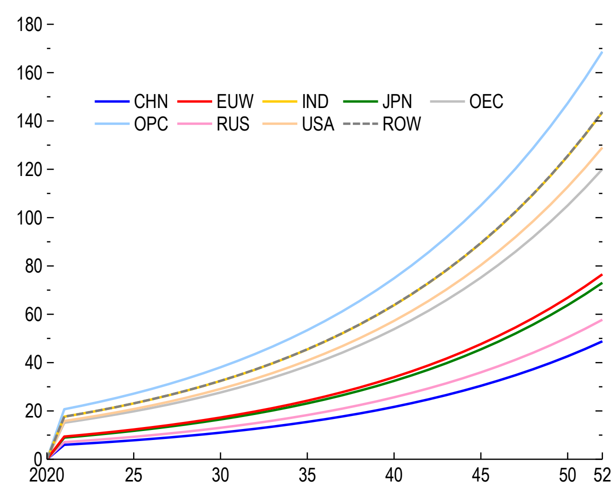
In the main results, we assume a constant growth rate of 7 percent for carbon taxes over the period of 2019-2050, and then solve the tax rates to achieve the emissions targets by 2050 in the policy package—after accounting for emissions reductions from other layers of the policy package (Annex Figure 3.4.2). For comparison, we also use a growth rate of 5 percent for carbon taxes and solve the tax rates to achieve the same targets by 2050.

Green Public Investment

We base our analysis on the results from Calderon, Moral-Benito and Serven (2015) who find that for every 10 percent increase in the aggregate stock of infrastructure capital, productivity in private sector output rises by 0.8%. We assume this new infrastructure once in place is sustained by spending by the government of 0.2% of GDP to offset depreciation. This locks in the productivity gains of the sectors that benefit from the green infrastructure. Rather than applying the improvement in productivity uniformly across all sectors in the economy, we assume that some sectors gain a productivity boost relative to others because of the strategic allocation of the infrastructure spending. We allocate the gains in productivity to these individual sectors. Once we assume which sectors receive the productivity boost, we scale the size of the productivity boost to those sectors in such a way that the aggregate productivity gains for the economy as a whole correspond to the results of Calderon and others (2015). For example, suppose the infrastructure is

Annex Figure 3.4.2. Carbon Tax

(US dollars per ton of CO_2, deviation from baseline)



Source: IMF staff calculations.
Note: Data labels use International Organization for Standardization (ISO) country codes. EUW = European Union, Norway, Switzerland, United Kingdom; OEC = Australia, Canada, Iceland, Liechtenstein, and New Zealand; OPC = selected oil-exporting countries and other economies; ROW = rest of the world.

focused mainly on the renewable energy sectors, then the productivity gains would be scaled up in these sectors so that when the shocks are weighted by the share of each sector in the economy, the aggregate productivity shocks match Calderon and others (2015). This implies that a small sector will have a very large productivity gain if all infrastructure is allocated to that sector. Because of capital adjustment costs, which are sector specific in the model, the economy-wide output gains will be lower than if the productivity was allocated across all sectors because rapid productivity growth increases the cost of accumulation private capital in the sector growing quickly.

Green Subsidy

We subsidize solar and wind output at a rate of 80% for all regions since 2019.

Avoided Damages from Climate Change

We introduce economy-wide productivity improvements driven by avoided damages from climate change due to all other policies in the package, and impose the productivity improvements equally on all sectors except electricity generation. The economy-wide improvements reflecting avoided damages from climate change are calculated using the extension of the Hassler and other (2020) integrated assessment model performed for this chapter (see Annex 3.5).

Carbon Tax Revenue Transfer 25%

We transfer 25% of carbon tax revenues to households as compensatory transfers to offset their loss of purchasing power from the carbon tax. The fraction of revenues needed for compensation was set at 25% based on the analysis in the section How to build inclusion (and Annex 3.7).

Aggregate Policy Package

This is the policy package including carbon taxes, green investment, green subsidy, avoided damages, and the carbon tax revenue transfer.

Aggregate Policy Package for Top 5 Countries

This scenario assumes that only the largest 5 countries (economic union) (USA, EUW, CHN, IND, JPN) participate in the policy package. For comparison with the aggregate scenario, we do not re-solve carbon taxes to achieve 80% reduction in the scenario, but directly use all shocks for the five countries/regions from the aggregate scenario.

Aggregate Policy Package for Advanced Economies Only

This scenario assumes that only advanced economies (USA, EUW, JPN, AUS, OEC) participate in the policy package. Similarly, we do not re-solve carbon taxes in the scenario.

Timing

Given that 2018 is the last year of observed data, the policy shocks are applied from 2019 onward. For presentational purposes, the simulation is presented as starting in 2021. This should not affect much the starting level of CO_2 emissions, as CO_2 emissions grew in 2019 but declined in 2020 due to the pandemic.

Annex 3.5. Climate Change Mitigation and the Direction of Technical Change

This annex outlines the model used to analyze the interaction between climate change mitigation policies and the direction (that is, the greenness) of technical change. This interaction is potentially important for two reasons. First, because the response of technological change to policy alters the effectiveness of mitigation policies, not only in the present but–because the direction of technical progress in the present affects the set of available technologies in future–also in future periods. Second, this channel expands the set of policies which can be analyzed, admitting a role for subsidies to research and development.

The model used here allows for the scale and direction of technical change to respond endogenously to policies, extending the model of Hassler and others (2020) in three important dimensions: adding a more general form of research and development (R&D) which allows for more flexible returns to scale; including non-unit price elasticity in final energy demand; and extending the range of fuel sources available to match IEA data. The resulting model framework is a useful laboratory for policy experiments, as it is rich enough to allow an analysis of the role of how the direction of technical change responds endogenously to policy but is tractable enough for the resulting outcomes to be comprehensible.

Conceptual Framework

We use a global integrated assessment model (IAM) in the spirit of Hassler and others (2020) (which itself follows in the tradition of earlier IAMS, such as Nordhaus 2010, and Golosov and others 2014). The global economy is modelled as several distinct regions, each producing a single energy good used as an input to aggregate domestic production. The energy good is made by combining fuels with a constant elasticity of substitution production technology. Fuel usage produces CO2 emissions, with different carbon intensities (the quantity of CO2 produced per unit of energy) for fuel in each region. Emissions in each region are therefore a function of both the total amount of energy used and its composition (green versus dirty). The sum of emissions across regions drives global temperatures via a climate model, which in turn reduces regional productivities, causing a climate externality.

Governments have two policy tools available to them to mitigate this climate externality: a tax on carbon, and a subsidy for research and development. Energy-producing firms conduct fuel-specific research and development (R&D), which lowers the input cost or the carbon intensity of fuel usage (or both). Firms therefore increase their R&D spending on a given fuel when the market for that fuel expands. Thus, policies which increase the market for a given fuel technology (say, renewable energy), spur further R&D in that technology, reducing costs and further amplifying the effect of the policy. There is also an inter-temporal spillover, as the cost of production is a function of research conducted in the past, as well as in the present. By stimulating research in the present, policies which lower the current cost of clean energy thus make clean energy more affordable in future.

The Energy Sector

Energy is produced by a CES technology using N fuels. Imported conventional oil is always indexed first. Energy production in region j in time t is therefore given by:

$$E_{jt} = \left(\sum_{i=1}^{N} \lambda_{i,j} e_{ijt}^{\rho}\right)^{1/\rho} \qquad (3.5.1)$$

where: g_{ijt} is usage of fuel *i* in region *j*; $\lambda_{i,j}$ is the production weight of fuel *i* in country *j*; and $\frac{1}{1-\rho}$ is the intra-fuel elasticity of substitution, common across all regions.

In each region, there is a fuel-specific technology for producing each fuel. At the start of each period *t* this technology is common knowledge.[20] The level of this technology is denoted $\bar{x}_{ijt}$, which represents the number of units of final good that are spent to produce one unit of input *i*. Firms can improve the technology they use via research, increasing this productivity to x_{ijt} at a cost:

$$r_i^x\left(x_{ijt}/\bar{x}_{ijt}\right) = \frac{\epsilon_{ij}(1-\chi_{ijt})}{\eta - 1}\left(\frac{x_{ijt}}{\bar{x}_{ijt}}\right)^{\eta-1}$$

where ϵ_{ij} is a region-specific cost parameter, and χ_{ijt} is the subsidy to R&D in fuel *i*. Crucially, $\eta > 1$, implying that this cost function is convex, and $\frac{1}{\eta-1}$ is the returns to scale in R&D. So as η declines, the returns to scale in R&D improve.

Technology similarly governs the carbon intensity of production, i.e. the amount of carbon dioxide produced per unit of energy. This is also common knowledge at the start of the period, denoted $\bar{g}_{ijt}$ and also improvable (i.e., reducing carbon intensity) via research, at cost:

$$r_i^g\left(g_{ijt}/\bar{g}s_{ijt}\right) = \frac{\theta_i j(1-\chi_{ijt})}{\eta - 1}\left(\frac{g_{ijt}}{\bar{g}_{ijt}}\right)^{1-\eta}$$

where θ_{ij} is also a region-specific parameter. Endogenous technical change therefore takes two forms: input-saving, and emissions-reducing. For simplicity we assume that the returns to scale and government subsidies across the two types are the same.

Letting $p_{ijt} = \frac{1}{x_{ijt}}$, the cost of production net of research is then:

$$\begin{aligned} c(e_1, \dots e_N, p_1, \dots p_N, g_1, \dots g_N) \\ = \sum_{i=1}^{N}(\tau_{jt} g_{ijt} + p_{ijt}) e_{ijt} + \frac{\epsilon_i(1-\chi_{ijt})}{\eta-1}\left(\frac{p_{ijt}}{\bar{p}_{ijt}}\right)^{\eta-1} \\ + \frac{\theta_i(1-\chi_{ijt})}{\eta-1}\left(\frac{g_{ijt}}{\bar{g}_{ijt}}\right)^{1-\eta} \end{aligned}$$

where τ_{jt} is the carbon tax for country *j* in period *t*.

[20] Fried (2018) shows that within-sector energy technology spillovers often occur within five years. As we later calibrate the model using a ten-year time period, assuming that the previous decade's worth of innovations are freely available to all firms is not unreasonable.

The cost of production defined above produces a downward-sloping average cost curve, meaning that energy production is a natural monopoly. This arises because research is a fixed cost; with increased sales, this cost is defrayed over more units, creating a cost advantage for larger firms and eventually resulting in a monopoly. For simplicity, we assume that energy supply is regulated so that the monopoly energy supplier makes zero profits. This can be implemented by a price cap such that the energy price equals the average cost. This is a not unreasonable assumption given frequent regulation of real-world energy markets. It is also a standard method for determining equilibrium a monopoly, and one which delivers the (static) socially optimal outcome without subsidies to energy production.[21]

This setting differs from the Hassler and others (2020) approach in two important ways. First, the cost of research is more general, allowing for returns to scale governed by the parameter η. Second, this approach allows for an aggregate market size effect. In the Hassler and others (2020) setting, the relative composition of research responds to relative market shares. In contrast, here total research also increases with total energy demand increases. This is potentially an important amplification channel for policy, as the impact on aggregate energy prices (and hence demand for energy) is a crucial mechanism by which mitigation policies work.

The advantage of this framework over a richer approach, such as Acemoglu and others (2016), is its simplicity. Changes in the composition of the energy bundle are determined by the relationship between the elasticity of substitution and the returns to scale in R&D (via an R&D composition effect); changes in aggregate energy usage are determined by a similar relationship between the elasticity of energy demand and the returns to scale in R&D (via an aggregate R&D effect).

Domestic Economy

The energy sector is an input into aggregate production. As the focus of the analysis is on the role of R&D in energy, the aggregate economy is kept deliberately very simple. Aggregate production is given by a CES aggregate of energy with a Cobb-Douglas energy bundle:

$$Y_{jt} = \phi_j(T_{t-1})\left(\left(1-\nu_j\right)\left((A_{jt}L_{jt})^{1-\alpha_j}K_{jt}^{\alpha_j}\right)^{\sigma} + \nu_j E_{jt}^{\sigma}\right)^{1/\sigma}$$

where ν_j is the energy share parameter for region *j*, α_j is the capital share for region *j*, A_{jt} is labor productivity, L_{jt} the labor force, K_{jt} the capital stock, and $\frac{1}{1-\sigma}$ is the elasticity of substitution of energy in final production. This last feature is an important further extension over Hassler and others (2020), as the elasticity of energy demand determines the aggregate response of energy usage to changes in the price of energy, such as those caused by climate mitigation policies.

The function $\phi_j(T_{t-1})$ is the region-specific damages from global temperature, assumed to be a function of temperature at the end of the preceding period, T_{t-1}. This determines the size

[21] The efficient outcome here requires a subsidy, the size of which is dependent on the slope of the demand curve.

of the climate externality and is allowed to vary by region given evidence that warmer countries typically have higher costs of climate change (see Nordhaus 2010, Dell, Jones and Olken 2014, Burke, Hsiang, and Miguel 2015).

Labor and capital are supplied in competitive markets. Labor is assumed to in fixed supply and grow exogenously over time. For simplicity, the capital stock is assumed to depreciate fully each period and to be owned by domestic households who have an inter-temporal elasticity of substitution equal to one. This means that saving is a fixed fraction of output, greatly simplifying the analysis.

International Economy

Following Hassler and others (2020), conventional oil is assumed to be produced at zero cost by an oil-producing region, which manages a fixed stock of oil reserves to maximize their monopoly rents. Unconventional (fracked) oil can be produced domestically. In equilibrium, the international price of oil moves to equate global oil demand with supply from the oil-producing region. The oil price is therefore the main international price linkage; there is no trade in other goods.

We allow for an international diffusion of ideas, modelled as a constant rate of catch-up by each region to the frontier level of technology.

$$\bar{x}_{ij,t+1} = \omega_j \bar{x}_{ijt} + \left(1 - \omega_j\right) \mathrm{max}_j \bar{x}_{ijt}$$

$$\bar{g}_{ij,t+1} = \omega_j \bar{g}_{ijt} + \left(1 - \omega_j\right) \mathrm{min}_j \bar{g}_{ijt}$$

Pollution and Climate Externality

Emissions in region *j* are

$$m_{jt} = \sum_{i=1}^{N} g_{ijt} e_{ijt}$$

and global emissions are

$$M_t = \sum_{j=1}^{M} m_{jt}$$

Past emissions contribute to the stock of global CO2 as in Golosov and others (2014), with:

$$S_t = \sum_{s=o}^{\infty} (1 - d_s) M_{t-s}$$

where the decay of absorption of emissions is parameterized by:

$$1 - d_s = \psi_L + (1 - \psi_L)\psi_0(1 - \psi)^s$$

The interpretation of this formulation is that for each unit of emissions, a fraction ψ_L remains in the atmosphere permanently, with the rest decaying at rate ψ. The evolution of emissions can therefore be expressed recursively using a separate variable for the permanent share of emissions.

Atmospheric and ocean temperatures, T_t and $\hat{T}_t$ respectively follow an energy budget model, derived from RICE/DICE (Nordhaus 2010). This is a linear coupled system with the stock of atmospheric CO2 acting as a forcing variable.

$$\begin{bmatrix} T_t \\ \hat{T}_t \end{bmatrix} = \begin{bmatrix} T_{t-1} \\ \hat{T}_{t-1} \end{bmatrix} + \begin{bmatrix} -\sigma_1(\hat{\eta}/\hat{\lambda} + \sigma_2) & \sigma_1\sigma_2 \\ \sigma_3 & -\sigma_3 \end{bmatrix} \begin{bmatrix} T_{t-1} \\ \hat{T}_{t-1} \end{bmatrix} + \begin{bmatrix} \sigma_1\hat{\eta} \\ 0 \end{bmatrix} 2^{\left(\frac{S_t}{S_{pre}}\right)}$$

where S_{pre} is the pre-industrial emissions stock, $\hat{\lambda}$ is the long-run climate sensitivity (the temperature increase due to a doubling of the atmospheric carbon stock), $\hat{\eta}$ determines the rate of convergence of temperature to the long-run level, σ_1 governs the auto-regressivity of atmospheric temperatures, and σ_2 and σ_3 capture the directed temperature exchange between the atmosphere and the oceans.

Productivity is a region-specific quadratic function of global temperature:

$$\phi_i(T_t) = 1 - \phi_i^0 + \phi_i^1 T_t + \phi_i^2 T_t^2$$

This cost function nests the specifications of Nordhaus (2010) and Burke, Hsiang and Miguel (2015), just with different specific parameter choices.

Model Solution

The state of the model is defined by the value of the region-specific labor productivity, capital, and fuel-specific technologies $\bar{x}_{ijt}$ and $\bar{g}_{ijt}$, as well as global stock of emissions and their permanent share. With nine productive regions and six improvable fuels this gives 128 state variables, justifying the strong simplifying assumptions on the structure of the macroeconomy.

Calibration

In order to match the G-cubed model (see Annex 3.4), there are ten regions, all of which have the production structure discussed above except for OPEC, which produces only oil for

Annex Table 3.5.1. Calibrated Production Parameters

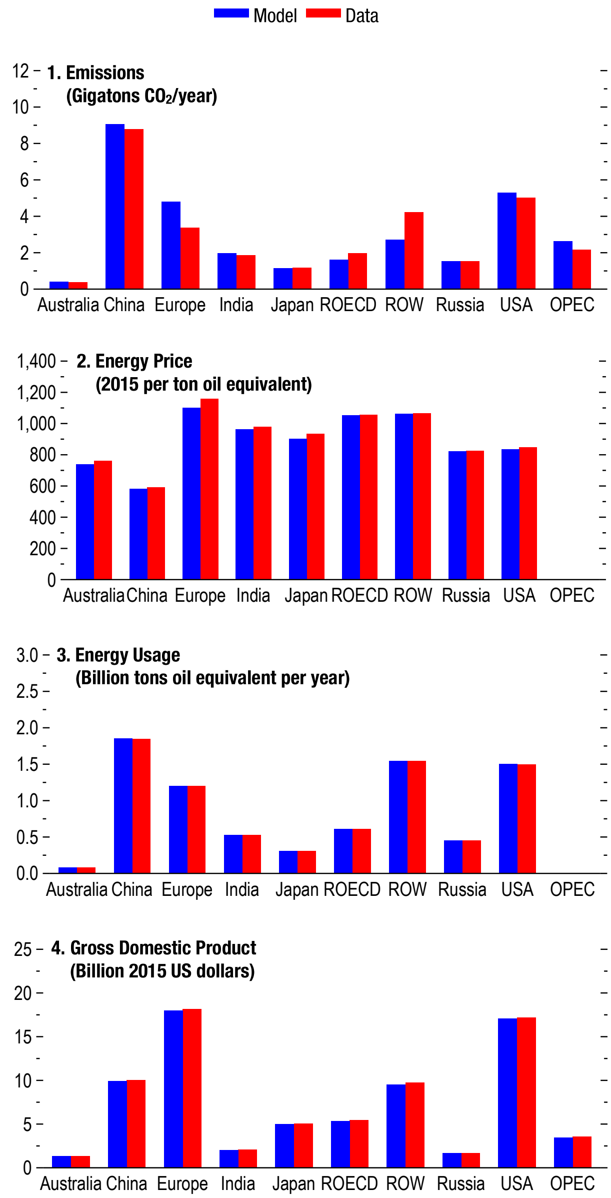
Parameter	Description	Type	Value	Target
$\lambda_{i,j}$	CES fuel weight	Regional		IEA fuel shares
ϵ_{ij}	Efficiency R&D cost shift	Regional		Regional fuel prices
θ_{ij}	Carbon intensity R&D cost shift	Regional		IEA carbon intensities
ρ	Intra-fuel CES parameter	Common	0.67	Papageorgiou et al. (2013)
η	R&D returns	Common	10	Fried (2018) dynamics
ν_j	Energy output share parameter	Regional		IEA energy shares
α_j	Capital share	Regional		WEO capital shares
σ	Aggregate CES parameter	Common	-3	Consistent with Annex 3.6

international trade. There are seven fuel types: international oil; domestic oil, natural gas, coal, hydroelectric, nuclear, and renewables. International and domestic oil are respectively identified with production via conventional and unconventional (e.g., fracking) methods of production.

The parameters of the aggregate and energy production functions are chosen to match data from the IEA on the usage, price, and carbon intensities of the different fuels (see Annex Table 3.5.1). The intra-fuel elasticity of substitution is set to three, consistent with Papageorgiou and others (2013), and the elasticity of substitution of energy and the capital-labor bundle is 0.25, in line with the assumptions of Annex 3.6. Returns to R&D are chosen to match aggregate responses of other models in the literature. Fried (2018) estimates that the innovation response in a model of endogenous technical change in the energy sector reduces by 20 percent the carbon tax required to meet a given reduction in emissions in 20 years. After accounting for key model differences, this implies returns to scale in R&D of around 0.11, or η of 10.

Aggregate production parameters are chosen to match the expenditure shares of energy, labor and capital. Initial values for capital and labor productivity are set to match average regional weights in global GDP and emissions during 2010-2019. Labor force growth is taken from ILO forecasts until 2030, and to converge smoothly to an annual growth rate of 0.2% by 2070, consistent with UN population projections. The long-run growth rate of labor productivity is assumed to be 1.3% per year, with catch-up growth in productivity in three regions (India, China, and RoW) during the short term. To capture trends in energy efficiency, the energy share parameter ν_j is assumed to decrease at around 0.7 percent annually, in line with recent trends.

Annex Figure 3.5.1. Results of Model Calibration, 2010–19 Average



Source: IMF staff calculations.
Note: OPEC is modeled as having only an extractive sector, so the usage and price of the composite energy is omitted. OPEC = Organization of the Petroleum Exporting Countries; ROECD = rest of Organization for Economic Co-operation and Development countries; ROW = rest of the world.

Annex Figure 3.5.1 compares the results of the calibrated model to the data, averaged across 2010-2019. Overall, the model matches the level and distribution of output, emissions, energy usage, and prices across the various regions.

The calibration of the climate module takes standard parameter values from Nordhaus (2010), Golosov and others (2014), and Hassler and others (2020). Baseline climate damages of higher temperatures are taken from Nordhaus (2010) with an alternative specification using Burke, Hsiang, and Miguel (2015).

Annex 3.6. The Macroeconomic Impact of Decarbonizing Electricity Generation

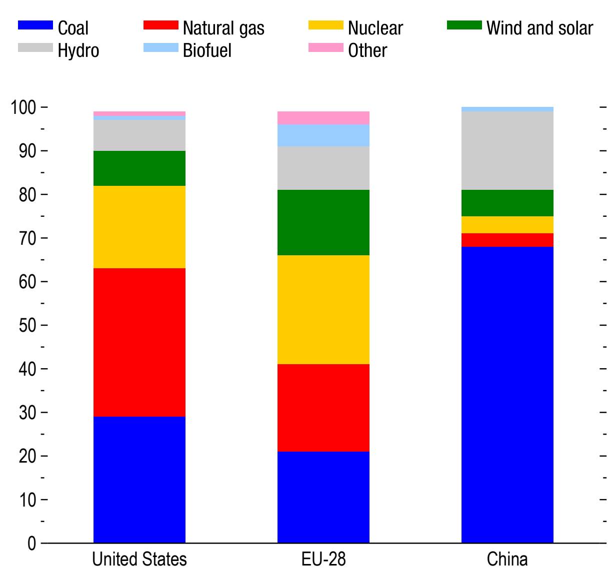
Carbon Emissions in the Electricity Sector

Emissions from electricity generation and heating amounted to roughly 40 percent of total global carbon dioxide (CO2) emissions in 2018 and are expected to grow further. Energy efficiency improvements will not be enough to offset the world's rising electricity needs due to projected economic growth and rising incomes in developing economies. Given current emissions trajectories and the electricity sector's role as key emitter, an immediate low-carbon transition is indispensable to avoid irreversible global warming. However, not only are currently adopted policies greatly insufficient to meet emissions reductions' targets from the Paris agreement, but policymakers' commitments for further electricity sector reforms in the future are generally estimated to fall short of what is needed to avoid irreversible climate damage. According to the International Energy Agency, the growth of low-carbon electricity sources up to 2040 under stated policies is estimated to be half as large as what is needed to meet the UN's Sustainable Development Goals and to cut emissions in line with the objectives of the Paris Agreement.

Electricity generation from coal dates to the 1880s and emits about one kg of CO2 per kWh, making it the heaviest-polluting electricity source that, by itself, causes roughly 30 percent of global CO2 emissions. The share of natural gas in the electricity mix has been rising in many countries, facilitated by an increase in supply from the fracking boom in the United States. With about 400 grams of CO2 per kWh, it is less polluting than coal–and so-called gas-for-coal switching lowered emissions in many countries–but emissions are still too high for gas to play a significant role in a low-carbon economy, aside from providing flexibility for backing up intermittent renewables.

Annex Figure 3.6.1 shows the electricity mix in the European Union, the United States and China. In all regions, the share of coal and natural gas is unsustainably high in the sense that absent a dramatic rebalancing, electricity generation will be a key driver of irreversible climate damage. The mix in the European Union is the least emitting, which is reflected in comparably low annual per-capita CO2 emissions from electricity and heating of 2,176 kg (as of 2017). However, coal still has a share of over 20 percent and is in many places backed by subsidies that delay the required transition. Per-capita emissions in the United States are about 2.5 times higher than in the EU (5,592 kg in 2017), which results from a per-capita electricity consumption about twice as large, combined

Annex Figure 3.6.1. Electricity Mix in 2018
(Percent of total electricity production)



Sources: International Energy Agency; and IMF staff calculations.

with a more polluting electricity mix in which coal and gas together make up over 60 percent of the generation. Electricity consumption in China is about 2/3 as large as in the EU, but the extremely high share of coal–almost 70 percent–elevates annual per-capita emissions to 3,312 kg.

Transition in the Electricity Sector

The need for an immediate transition towards low-carbon electricity raises questions about its technical feasibility, its costs, and the role governments can play in its facilitation. Feasibility has improved dramatically over the last decade, with prices for key renewable technologies having undergone a rapid decline that is expected to continue. This made them economically viable and gave them the potential to replace coal-fired electricity on a large scale. The improved competitiveness of renewables means that the balance between low and high-carbon technologies can be more easily tipped in favor of the sustainable kind, and thereby creates the conditions for mitigation policies to be especially effective. This is crucially different from a decade ago when limited technology readiness constrained the effectiveness of the green stimulus provided after the Global Financial Crisis in decarbonizing electricity generation (IEA, 2020c), suggesting that that episode may offer little guidance on the likely impact of mitigation policies at the current juncture. The following analysis shows that in the current technological environment mitigation policies can lead to substantial reductions in emissions. The associated macroeconomic costs are modest and, under any reasonable probability distribution, dwarfed by the costs of global warming. Governments thus must seize the opportunity and play a key role in accelerating the transition that, left to market forces alone, will come too late. This holds especially at the current juncture characterized by low interest rates and the need for economic stimulus to stabilize demand during the Covid-19 crisis.

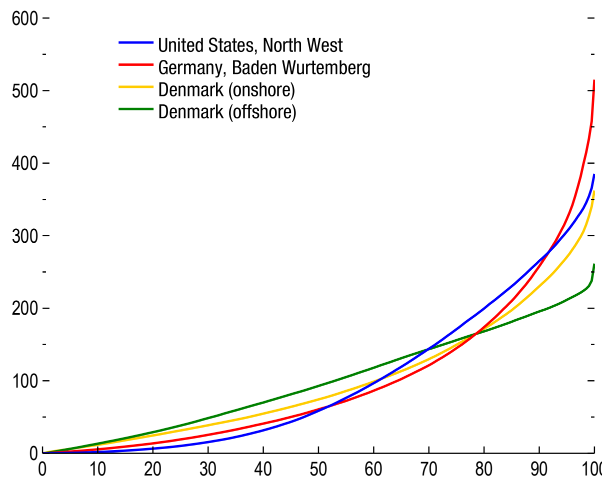
There are various low-carbon technologies to produce electricity. Each has its specific advantages and drawbacks, and it is difficult to predict how technology will evolve in the future. Hydraulic power generation has geographic requirements that limit the availability of sites and causes broader environmental damages. Biomass can be used to generate electricity, but its production could compete with other uses of land. Nuclear power is a carbon-neutral technology with a scalability that would allow to replace coal and gas but has a generally low popularity. The latter results from a combination of recent nuclear disasters, the prominent discussion of nuclear waste management, and an underappreciation of its potential to curb global warming when it replaces high-carbon technologies. In actuarial terms however the costs of nuclear power–a low probability of devastating but geographically limited damage–will likely be dwarfed by the certain, global and irreversible damages from climate change. The most promising and politically acceptable carbon-neutral technology is renewable electricity generation from wind and solar photovoltaic (PV). The key drawback of this technology, discussed in detail below, is that electricity from renewables is intermittent, i.e. that it is only generated when there is wind or sun. Carbon capture and storage (CSS) technologies have the potential to reduce emissions from coal power plants, but a significant deployment of this technology is prevented by high costs that are not predicted to fall substantially in the near term. In this analysis we focus on renewables as the technology to bring about an electricity transition, as it is in principle scalable and, relative to nuclear power, politically less controversial.

Intermittency of Wind and Solar

Our focus on renewables merits a closer inspection of its intermittency problem. Annex Figure 3.6.2 shows so-called generation duration curves for different illustrative regions, i.e. the electricity output from wind as a function of wind regimes ordered by their strength. The data is normalized by average electricity output over time so that, for example, the curve for the US Northwest tells us that output during the top 20 percent of the time exceeds twice the average output. We observe that there are substantial periods in which wind generates close to no output. The load factor (i.e. the ratio between average generation and peak generation) of the shown data is between 35 percent for onshore wind and 45 percent for offshore wind. For solar PV, it amounts to about 25 percent.

Annex Figure 3.6.2. Generation Duration Curve for Electricity from Wind

(Percent of average production over a year; percent of generation duration on x-axis)



Sources: Bonneville Power Administration; EnergyNet; TransnetBW; and IMF staff calculations.

Thus, to ensure that electricity supply can always meet demand, either demand must be managed to decline in line with supply when renewable output is low, or total electricity supply must be stabilized in the face of output fluctuations from renewables. Demand management on the part of private households and industrial production has potential but is still insufficient to solve the problem of intermittency. Electricity storage could smooth out output fluctuations and is developing rapidly but is not yet ready to be deployed at a sufficiency large scale. The most prominent example for utility-scale electricity storage are hydro-pumps, whose global power capacity the International Hydropower Association estimates at 158 GW. In the United States, the European Union and China (IHA, 2020), this would represent about 30 minutes of power consumption, while managing solar (wind) intermittency would require about 18 hours (72 hours) of electricity storage. Chemical storage (batteries or hydrogen) are still too expensive for large deployment and other technologies based on heat or gravity are not mature yet. With electricity storage still not being economically viable at a large scale, the intermittency of renewables must be compensated by other flexible electricity sources in the grid. Natural gas and hydro are the most commonly used for this purpose. The International Energy Agency points to flexibility retrofits that can potentially allow coal power plants to serve as a backup for renewables (IEA, 2019). While this can give existing power plants a role in an electricity transition, it would entail a slower decline in emissions relative to the use of other backups.

The constraints that intermittency poses for the expansion of renewables are captured by a dedicated module of our macroeconomic model introduced below. Under the assumption that demand flexibility and electricity storage are not yet sufficiently mature to manage intermittency, the model requires that any intermittent generation capacity is paired with a dispatchable backup capacity that is idle for most of time but can cover power shortfalls of intermittent technologies (see Morris and others, 2010). More precisely, the backup covers, at any point in time, the difference between intermittent power generation and the desired output. Pairing renewables with a backup increases costs relative to stand-alone renewables, but fully compensates for their drawback of being intermittent. The framework allows for so-called overcapacity, i.e. the installation of renewable capacity that, at peak output, produces electricity above demand that must be curtailed.

The Optimal Renewables-Backup Mix

Generation duration curves as show in Annex Figure 3.6.2 can be well approximated by the power function

$$E = p^{\gamma}$$

where γ is a parameter measuring the degree of intermittency (the corresponding load factor is given by $1/(1+\gamma)$). Offshore wind is generally more stable than onshore wind, reflecting in an intermittency parameter of between 1 and 1.5, compared to values between 2 and 3 for onshore wind. Solar intermittency has a different intermittency profile—it does not produce at night—but has a similar pattern as wind during the day.

Variable costs of the backup, fixed costs of renewables, and fixed costs of the backup are denoted by C^{v}, C^{fr}, and C^{fb} respectively. We assume that a utility using renewables paired with a backup aims to produce a constant output L. The size of the backup capacity relative to renewable capacity is endogenously determined by cost-minimization based on γ (as the degree of intermittency influences the need for a backup) and the costs structures of both technologies. To build intuition for the choice a utility faces, we first consider the illustrative case in which there is a given backup capacity but no renewables. Deploying renewables—operating at zero variable costs—lowers the utility's overall variable costs, as costly generation from the backup can be substituted for. Under our assumptions on the cost structure after taxes and subsidies, variable cost savings from expanding renewables exceed their installation costs, so the utility chooses to increase renewable capacities at least up to the point where peak renewable output equals L. Expanding renewables above this point still lowers variable costs by reducing the share of output from the backup, but the variable cost savings are declining in size because of curtailment: since peak renewable output now exceeds L, a positive share of renewable output has to be curtailed. Because of the shape of the generation duration curve, this share rises at an increasing pace when additional renewable capacity is installed. At the cost-minimizing ratio between renewable and back-up capacities, curtailment reduces the variable cost savings from additional renewables such that they equal the fixed costs. Optimality implies that the following output B is produced from the backup (and the remainder $L - B$ from renewables):

$$B = \frac{\gamma}{1+\gamma}\left(\frac{C^{v}}{C^{fr}}\right)^{\frac{-1}{1+\gamma}}$$

Model Description and Calibration

The analysis uses the Carbon Mitigation Macro Model (CarMMa), a Dynamic Structural General Equilibrium (DSGE) model tailored for analyzing how governments can trigger an electricity transition and its macroeconomic implications. Such analysis implies two key modelling requirements. First, a detailed description of the government and the macroeconomy is necessary to capture the fiscal dimension of policies and their general-equilibrium effects. CarMMa meets this requirement as it largely builds on the IMF's workhorse model GIMF and inherits a detailed description of the interaction between households, firms, a detailed fiscal sector and monetary policy, as well as a menu of real and nominal rigidities. CarMMa is currently a closed-economy model. The second modelling requirement is that the electricity sector should be sufficiently granular to capture technology-specific practical constraints to an electricity transition. CarMMa's electricity sector encompasses four technologies: coal, natural gas, renewables, and nuclear power plus hydro. The fuel required for coal and natural gas generation is mined in two specific mining sectors. Nuclear and hydropower have negligible carbon emissions and close to zero marginal cost. Hydro and nuclear capacities are exogenous, reflecting limited availability of hydropower sites and the crucial role of political considerations, rather than market-based ones, in the development of nuclear power. When nuclear power expands, building additional capacities is subject to a time-to-build constraint. Due to intermittency, renewables are paired with a backup capacity in a cost-efficient manner as outlined above. The most common backups are hydropower and natural gas, while coal (assuming appropriate flexibly retrofits) comes third according to a merit-order model. Different electricity generations compete on a commodity market for electricity where output from the different sources are treated as very close substitutes (they are equally dispatchable, as intermittency from renewables is compensated by the backup). For the US model, natural gas is assumed to be the only backup, whereas both natural gas and coal are used as backup in China and the European Union (to capture the shortage of natural gas in both regions). Electricity is used as an intermediate input in the production of manufacturing goods and services, and also directly enters the final consumption good.

The structure of GDP by sector (electricity, manufactured goods and services), by expenditure (private consumption and investment as well as public consumption and investment), and by income (total compensation, gross operating surplus and taxes and subsidies) reproduces national accounts in 2018 and the most recent input-output tables. The share of the different electricity-generation technologies and their emissions (abstracting from those associated with the installation and dismantlement of capacity) reproduce data from the IEA. Flexible generation from hydropower and the development of offshore wind can to some

Annex Table 3.6.1. Electricity Generation and Use
(Percent of GDP)

	United States	European Union	China
Electricity	1.9	3.0	2.3
Manufacturing	0.4	0.9	1.2
Services	0.5	0.7	0.6
Consumption	1.0	1.4	0.5

extent alleviate the intermittency problem, which we do not explicitly model but proxy for by using an intermittency parameter γ lower than observed. Annex Table 3.6.1 shows for the three regions the share of electricity generation in output, and the breakdown of electricity use between final consumption and as input in manufacturing and services.

Impact of the Introduction of a Carbon Price

Before turning to the simulation results, we highlight key aspects of the transmission of a carbon price into the electricity price, and of the electricity price into macroeconomic variables.

Transmission of a Carbon Price into the Electricity Price

When a carbon price is introduced, the mining sector absorbs some of the carbon price burden, which cushions the rise in fuel costs experienced by coal-based (and to a lesser extent gas-based) electricity producers. A carbon price reduces fuel demand and thereby the price of coal and gas, at least in the short run, so that electricity producers do not face a one-for-one increase in fuel cost. The impact of a given rise in fuel costs on the electricity price is further dampened by the competition in the market. The carbon price increases fuel costs of electricity generation from coal (and gas) but has no impact on marginal costs of other technologies. Given the high degree of competition, coal and gas producers are not able to significantly increase prices despite rising fuel costs. Some of the required room for absorbing higher costs results from a decline in investment, which, in turn, follows from expected permanently reduced profitability. A further factor mitigating the adjustment of the electricity price is the rebalancing of the electricity mix. A carbon price tilts relative prices to the disadvantage of carbon-intensive technologies and thereby triggers a gradual transition towards low-carbon technologies. The associated decline in the average carbon intensity of the electricity mix means that a given carbon price leads to a smaller increase in the electricity price. The strength of this effect depends on the availability of natural gas as a backup: If gas is scarce and a more carbon-intensive technology has to be used as backup, a given surge in renewables implies a weaker decline in emissions and thereby in the carbon price burden.

Transmission of a Higher Electricity Price into the Macroeconomy

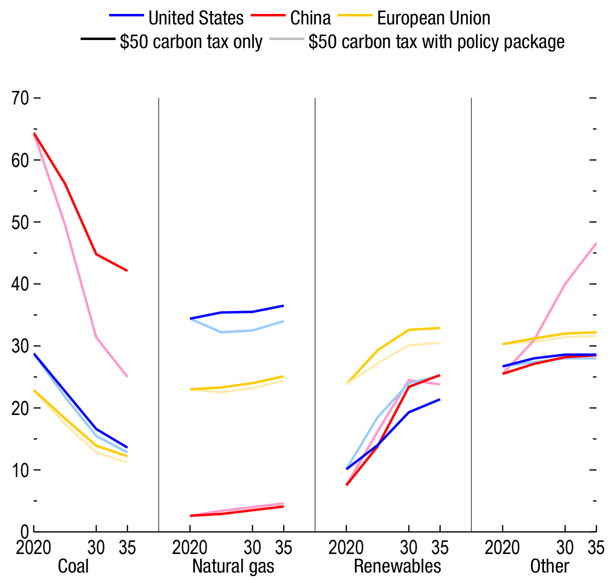
Electricity is used to operate machines (or buildings) that increase labor productivity. A higher electricity price does not significantly alter technical coefficients, so firms have limited means to substitute capital and labor for electricity when the latter becomes more costly, but instead reduce demand for capital and labor. Due to the high price elasticity of capital supply and the low price elasticity for labor in general equilibrium, the decline in demand translates into a reduction of investment and capital accumulation (implying that a higher investment share increases the impact of a carbon price on output), as well as into lower real wages. This causes the impact of a carbon price to affect sectors beyond electricity production. The strength of these spillovers is determined by the elasticity of substitution between electricity and other factors, which we set to 0.3, and by the share of electricity in the respective sector.

In a nutshell, the macroeconomic impact of a carbon price in the electricity sector depends on four factors: the initial share of coal in the electricity mix, the portion of the carbon burden that is absorbed by the mining sector, the availability of low-carbon backup technologies, and the investment share in the economy.

Carbon Price of 50USD in the United States, the European Union and China

We first study the gradual introduction of a carbon price, phased-in over 10 years, in the United States, China and the Euro Area, under the assumption that carbon tax revenues are given back to households as transfers. Lines in darker colors in Annex Figure 3.6.3 show the adjustment of the electricity mixes in this scenario. Annex Figure 3.6.4 shows in the same fashion the adjustment of output, investment, consumption and electricity-related CO2 emissions. In the interpretation of output costs, we need to consider that the model does not account for climate damages and therefore does not capture benefits from cutting emissions.

Annex Figure 3.6.3. Decarbonization of the Electricity Sector: Adjustment of Electricity Mixes
(Percent)



Source: IMF staff estimates.
Note: Simulation of a $50 tax per ton of carbon dioxide, phased in over 10 years, alone and together with a policy package. The policy package includes, in each of the three regions, front-loaded renewables investment subsidies and, in the short term, an accommodative monetary policy. For China, the policy package also includes a doubling of nuclear and hydro capacities over 20 years.

The carbon price discriminates by the carbon-intensity of the different technologies and thereby tilts relative prices to the disadvantage of coal and, to a lesser extent, natural gas. This results in a decline in the share of coal generation in all regions. In the United States, the share falls below 10 percent as natural gas is abundant enough to provide the grid sufficient flexibility to accommodate the rising share of renewables. Our assumption of an average 40-year lifetime of a coal power plant slows down the transition, as the immediate collapse of investment in that sector only translates into a gradual depreciation of the capital stock. In the European Union and China, the use of coal alongside gas as a backup for renewables mitigates to some extent the decline of the share of coal. As a result of introducing the carbon price, the electricity price rises gradually to reach a cumulative increase after ten years of 10 percent in the European Union, 20 percent in the United-states and 30 percent in China where the share of coal is the highest.

The carbon price reduces investment, as a result of shrinking coal sectors, as well as lower economy-wide investment due to the limited extent to which manufacturing goods and services producers can substitute away from more costly electricity. After an initial uptick caused by higher dividend pay-outs associated with less spending on investment, consumption declines. GDP declines gradually over ten years (relative to baseline), implying an average annual growth reduction of about 0.1 percentage point in the United-States and European Union, and 0.3 percentage point in China. The larger decline in China has two main explanations. First, the larger share of coal in the electricity mix amplifies the rise in the electricity price; and second, the high share of investment in the economy means that a given decline in investment translates into a greater drop in aggregate demand and output. Given its dampening impact on investment, the carbon price works towards rebalancing the economy towards a larger consumption share.

After ten years, carbon emissions in the electricity sector have declined relative to baseline by about 30 percent in the European Union, 35 percent in the United States, and 38 percent in China. Electricity-related emissions in China and in the United States decline by roughly the same proportion after ten years, but different initial emission levels cause the declines to differ in absolute size (745 megatons in the United States, 390 megatons in the EU, and 1919 megatons in China).

Carbon Tax with a Macro Package in the United States and the European Union

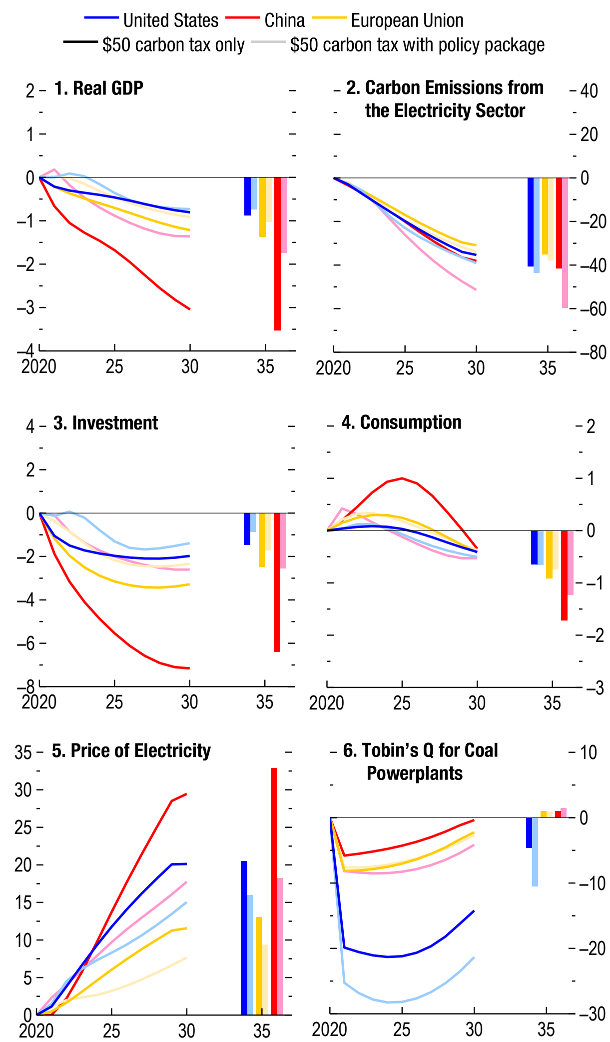
The additional government revenues generated by the carbon price offer the chance to foster the further development of renewables. For the United States and Europe, we consider a macro package that complements the carbon price with (i) frontloaded subsidies for investment in renewables, financed by public debt in the first five years, and (ii) accommodative monetary policy in the short run. In the United States, initial subsidies amount to 60 percent of the investment costs in renewables, and then decline to 30 percent after five years. In the European Union, the rate starts at 40 percent and declines to 20 percent after five years, reflecting lower carbon price revenues compared to the United States. The subsidies boost investment in the short term and thereby accelerate the electricity transition, which, by lowering the average carbon intensity, dampens the impact of the carbon price on the electricity price and GDP. Note that renewables investment subsidies come in addition to existing renewables production subsidies, which are incorporated in the initial calibration.

Lighter lines in Annex Figure 3.6.4 denote the adjustment when the macro package complements the introduction of the carbon price. The macro package compensates the output decline the short run and mitigates the decline of output in the long run, while it also amplifies the reduction in emissions. The effectiveness of the macro package is greater when it is paired with a carbon price. The reason is that the prospect of a higher long-run market share of renewables (brought about by the carbon price) amplifies the impact of a given subsidy.

Carbon Tax with a Macro Package and Additional Nuclear Power in China

China's strong reliance on coal amplifies the macroeconomic costs of introducing a carbon price. To investigate to what extent these costs can be mitigated by additional policies, we study a broader policy mix which, next to the gradual introduction of a 50 USD carbon tax, also features an expansion of nuclear power and an improved availability of natural gas (which can be used as backup for renewables). Annex Figure 3.6.4 compares the impact of this policy mix to the impact of the isolated 50 USD carbon price (from the previous exercise). The additional measures cut output costs by roughly a half and amplify the decline in emissions by about 50 percent. The deployment of additional nuclear power capacity immediately contributes to the decline in emissions, as additional supply leads to a crowding-out of other producers in the grid, which are mostly coal-based. The subsidy for natural gas generation leads to deployment of new capacities that can serve as backup for renewable generation. As a result, the surging need for a flexible backup capacity–brought about by the rising share of renewables triggered by the carbon price–is split between coal and gas. This further amplifies the decline in the coal share. A key reason for the mitigation of the output decline is that the additional measures partially offset the increase in electricity costs caused by the carbon price. There is a direct channel by which nuclear power immediately increases supply of electricity and lowers the price, as well as an indirect channel based to the rebalancing of the electricity mix: the reduction in the share of coal caused by the additional nuclear and natural gas capacity lowers the average carbon intensity of electricity generation, which in turn dampens the price increase caused by the carbon price.

Annex Figure 3.6.4. Decarbonization of the Electricity Sector: Macroeconomic Impact
(Percent deviation from baseline)



Source: IMF staff estimates.
Note: Simulation of a $50 tax per ton of carbon dioxide, phased in over 10 years, alone and together with a policy package. The policy package includes, in each of the three regions, front-loaded renewables investment subsidies and, in the short term, an accommodative monetary policy. For China, the policy package also includes a doubling of nuclear and hydro capacities over 20 years.

Policy Implications Beyond the Model Analysis

The large number of existing coal power plants and their young average age (60 percent are

20 years or younger) are a key concern for the practical implementation of an electricity transition. Continued operation of the existing fleet would generate enough emissions to potentially put sustainable development targets out of reach (International Energy Agency 2019), but a rapid retirement of that capacity could impose financial losses to their owners, who often include governments. The IEA estimates that existing coal power plants represent globally more than $1 trillion unrecovered capital investment. In the model simulations, this aspect surfaces in a dramatic decline in the value of coal power plants–summarized by Tobin's Q of the respective capital stock. This raises the question of how an electricity transition can be designed to minimize financial damages. The International Energy Agency points to the possibility of retrofitting and repurposing a significant share of existing plants, especially younger and more efficient ones, to make their continued operation compatible with climate targets. Possible retrofitting options include installing equipment for CCUS (Carbon Capture, Utilization, and Storage) or biomass co-firing, while repurposed plants can continue their operation at lower utilization levels to provide flexibility and thereby facilitate an expansion of intermittent renewable sources.

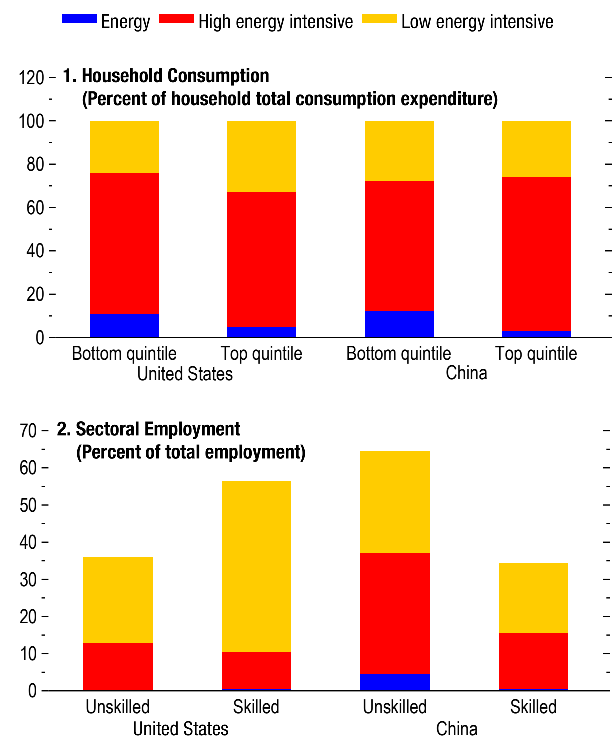
Annex 3.7. How to Avoid A Further Widening in Income Disparities and Build Inclusion?

Understanding the impact of carbon taxes on income inequality is critical to galvanizing support to fight climate change. Achieving inclusive climate change mitigation policies requires a thorough understanding of the channels through which carbon taxes affect the income distribution and the magnitudes in question.

Carbon taxes can worsen income inequality because low-income households spend a proportionately larger fraction of their income on high-energy intensive goods, a fact that has been explored extensively in the literature (see Grainger and Kolstad 2010, Fremstad and Paul 2019, and IMF 2019 for examples).[22] However, another important fact that is less known is that carbon taxes can also worsen income inequality by affecting proportionately more the wages and job opportunities of unskilled low-income workers. Unskilled workers are more likely to work in the high-energy intensive sector that is impacted more by a carbon tax (Annex Figure 3.7.1).[23,24]

In this section, a model that captures both the consumption and employment impacts of a carbon tax is developed. The model is used to quantitatively analyze the effect of a 50 USD per ton of CO2 tax on income inequality, considering different uses of the carbon tax revenue. Four different revenue recycling cases are examined in the analysis: (i) the carbon tax revenue is used to finance spending on the low-energy intensive

Annex Figure 3.7.1. The Distribution of Consumption and Employment



Sources: American Community Survey; China Family Panel Survey; Consumption Expenditure Survey; National Bureau of Statistics of China; and IMF staff calculations.
Note: Energy goods are electricity, heating, gas, and oil. High-energy-intensive goods are mostly industrial goods and transportation, while low-energy-intensive goods are basically services. Unskilled workers are workers with a high-school education or less, while skilled workers have more than a high-school education.

[22] There are examples where carbon taxes can improve income inequality, in these cases high-income households spend a relative larger share of income on energy-intensive goods. This is sometimes the case in EMs and LIDCs, where poor households do not have access to electricity. In these cases, carbon taxes can be progressive instead of regressive, but they may also reduce future access to electricity for poor households. IMF (2019) finds that this is the case for India.

[23] Chateau and others (2019) analyzes the impact of a carbon tax across occupations in a Computational General Equilibrium model (CGE) and find that low-skilled occupations are more likely to be negatively affected by carbon taxes. Marin and Vona (2019) use a shift-share instrumental variable approach applied to 14 European countries and shows that climate policies have been skill-biased against manual workers and have favored technicians.

[24] An important limitation of this data is the inability to account for the share of employment in clean energy production. This is an issue that has been documented extensively in the literature (see for instance US Department of Energy 2017).

good; (ii) the carbon tax revenue is used finance a universal cash-transfers program; (iii) the carbon tax revenue is used to finance a targeted cash-transfers program for the bottom two quintiles of the income distribution; and (iv) the carbon tax revenue is used to fund a subsidy to clean energy consumption "feebates".

Model

This analysis uses a multi-sector heterogeneous agent model to simulate the impact of the various policies on income inequality. More details about the model and calibration can be found in Tavares (2020). The model is a small open economy with four goods (high-energy intensive good, low-energy intensive good, dirty energy, and clean energy) and two household types (skilled and unskilled). The high-energy intensive good and the low-energy intensive good are produced using capital, high-skilled labor, low-skilled labor, dirty and clean energy. The use of inputs differs across sectors: the high-energy intensive sector is more energy and low-skilled labor intensive than the low-energy intensive sector. Dirty and clean energy are produced using low-skilled labor and capital, and clean energy is more labor-intensive than dirty energy.[25]

There are two types of households: skilled and unskilled. Skilled and unskilled households differ in their average productivity and the sectors in which they can find employment. Skilled and unskilled households have the same preferences over the consumption of the high-energy intensive good, the low-energy intensive good, dirty energy, clean energy, and leisure. They face idiosyncratic productivity shocks that they can partially insure against by investing in a risk-free asset.

The two key features of the model are that: (i) household preferences are non-homothetic; and (ii) the skilled and unskilled labor-intensity varies across sectors.

Preferences

Non-homothetic preferences imply that low-skilled and low-income households consume a larger share of energy and energy-intensive goods in their consumption basket because their income is lower. Households in the model maximize expected lifetime utility over the consumption of the low-energy intensive good c^l, the consumption of the high-energy intensive good c^h, energy e, and hours worked l, subject to the borrowing constraints.

Households' utility function is given by

$$u(c^l, c^h, e, l) = \psi_l \log(c^l + \bar{c}^l) + \psi_h \log(c^h) + (1 - \psi_l - \psi_h) \log(e - \bar{e}) - \chi \frac{l^{1+\frac{1}{\gamma}}}{1 + \frac{1}{\gamma}}$$

where e is the consumption of energy. The latter is a composite of clean e^c and dirty e^d energy given by

[25] Despite its richness, this model abstracts from some channels that have been explored in literature. These include for example, the impact of carbon taxes on capital income (Metcalf 2019), informality (Bento and others (2018), and differences across ages and cohorts (Fried and others 2018).

$$e = \left(\mu^e (e^c)^{\rho^e} + (1-\mu^e)(e^d)^{\rho^e}\right)^{1/\rho^e},$$

where ρ^e determines the elasticity of substitution between clean and dirty energy. The term $\bar{e}$ captures that the energy is a "subsistence" good that is consumed disproportionally more by low-income households while $\bar{c}^l$ is a "luxury" good that is consumed disproportionally more by high-income households.

The household budget constraint is given by

$$p^h c^h + p^l c^l + p^c e^c + (1+\tau)p^d e^d + \; b' \leq w \quad l \quad z \quad + (1+r)b + T(w^k l^k s^k),$$

where p^h is the price of the high-energy intensive good, p^l is the price of the low-energy intensive good, p^c is the price of clean energy, and p^d is the price of dirty energy. b is the risk-free asset, r is the risk-free interest rates w is the workers' wage that depends on skill level, z denotes the current idiosyncratic productivity shock, and $T(\cdot)$ is the government transfers.

Production

Differences in the labor intensity across sectors imply that unskilled households are more likely to find employment in the high-energy intensive sector. High and low-energy intensive goods are produced using constant elasticity of substitution (CES) production functions given by

$$f^j\left(K^j, L^{s,j}, L^{u,j}, E^{c,j}, E^{d,j}\right) = A^j \left(\mu_k^j \left(K^{\alpha^j} L^{1-\alpha^j}\right)^{\rho_k^j} + (1-\mu_k^j)\left(E^j\right)^{\rho_k^j}\right)^{\frac{1}{\rho_k^j}}$$

where K^j is the capital; L^j is the aggregate effective labor input, which is a combination of effective skilled $L^{s,j}$ and unskilled labor $L^{u,j}$; and E^j is a combination of clean energy $E^{c,j}$ and dirty energy $E^{d,j}$. These are given by

$$L^j = \left(\mu_l^j \left(L^{s,j}\right)^{\rho_l^j} + (1-\mu_l^j)\left(L^{u,j}\right)^{\rho_l^j}\right)^{\frac{1}{\rho_l^j}} \text{ and } E^j = \left(\mu_e^j \left(E^{d,j}\right)^{\rho_e^j} + (1-\mu_e^j)\left(E^{c,j}\right)^{\rho_e^j}\right)^{\frac{1}{\rho_e^j}}$$

where $j \in \{h, l\}$. The key assumptions in the model based on data analysis is that the high-energy intensive sector is more energy-intensive than the low-energy intensive sector (e.g. $\mu_k^h < \mu_k^l$) and the high-energy intensive sector is more intensive in unskilled labor than the low-energy intensive sector (e.g. $\mu_l^h < \mu_l^l$).

Equilibrium

The household state variables, x, are asset holdings, b, and idiosyncratic labor productivity, z. Given the distribution of skilled and unskilled workers μ, carbon tax τ, interest rates r, a utility function $U : R_+ \times R_+ \times R_+ \times R_+ \rightarrow R$, factor prices $\{w^s, w^u, r, p^h, p^l, p^c, p^d\}$ and capital depreciation rate δ, a stationary competitive equilibrium consists of workers' decision rules $\{c^{j,l}, c^{j,h}, e^{j,c}, e^{j,d}, l^j, b'^{,j}\}_{\{j\in\{u,s\}\}}$, goods firms' production plans $\{K^j, L^{j,s}, L^{j,u}, E^{j,d}, E^{j,c}\}_{\{j\in\{h,l\}\}}$, energy firms' production plans $\{K^j, L^{u,j}\}_{\{j\in\{c,d\}\}}$, and the distribution of agents, $\Gamma(x)$, such that the following holds:

- Given prices and policies, a household with skill level *j* maximizes lifetime expected utility subject to the borrowing constraints.
- Goods producer *j* demands for K^j, $L^{j,s}$, $L^{j,u}$, $E^{j,d}$, and $E^{j,c}$ satisfy the firm optimization problem.
- Energy producer *j* demands for K^j and $L^{j,u}$ satisfy the firm optimization problem.
- The government budget constraint is satisfied.
- Skilled and unskilled labor markets clear.
- The low-energy intensive good market clears.
- The distribution $\Gamma(x)$ is stationary.

Calibration

The model is calibrated to the data by matching the households' consumption composition by income level to sectoral energy-intensity. The calibration uses the Consumption Expenditure Survey (CEX) to match consumption in the United States and the China Family Panel Survey (CFPS) for China. Using these two data sets, consumption goods are divided into three main categories: Energy (primarily utilities and gas), high-energy intensive goods (industrial goods and transportation), and low-energy intensive goods (services less transportation). To match the three sectors to workers, the calibration uses data from the American Community Survey (ACS) for the United States and data from the National Bureau of Statistics of China (NBS) for China in order to measure the skill intensity of the different sectors of the economy. Finally, each sector's energy intensity is calibrated using data from the International Energy Agency (IEA). All the elasticities of substitution are taken from the literature and are assumed to be the same in the United States and China.[26]

Results

To examine the distributional impact of a carbon tax, this section simulates the baseline economy with no carbon tax and then conducts a series of counterfactual experiments in which a constant carbon tax set at 50 USD per ton of CO2 is imposed. In particular, three different policies that differ in how the government recycles the carbon tax revenue are considered. In the

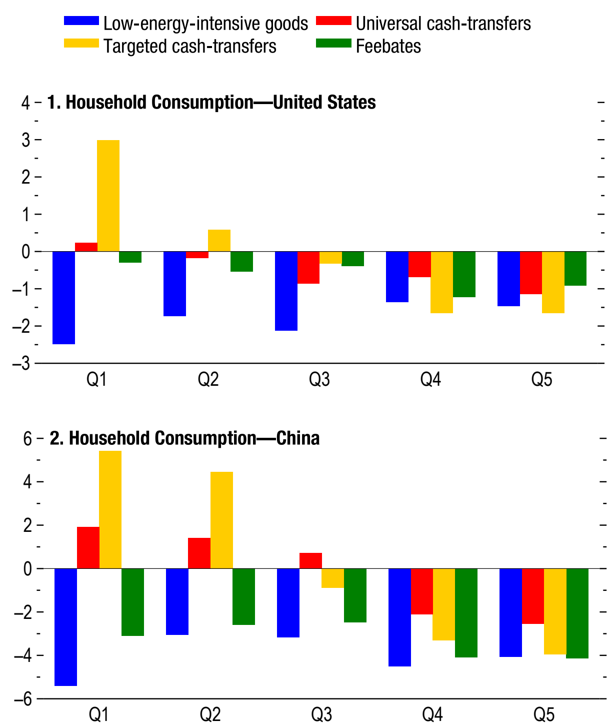
[26] There are three critical elasticities of substitution in the model. The elasticity of substitution between clean and dirty energy is selected to be equal to 3 in the range estimated by Papageorgiou and others (2013). The elasticity of substitution between energy and the capital-labor composite is selected to be equal to 0.25 in the range estimated by Van Der Werf (2008). The elasticity of substitution between skilled and unskilled labor is selected to be equal to 2, in the range estimated in the literature and discussed in Acemoglu and Autor (2011).

first case, the government uses the revenue to finance government spending on low-energy intensive goods. In the next two cases, the government uses the revenue to finance, respectively, a universal cash-transfer program, and a cash-transfer program targeted to the bottom two quintiles of the income distribution.

This section's main result is that without compensatory measures, carbon taxes lead to an increase in income inequality measured by the Gini coefficient (Annex Table 3.7.1). Income inequality increases because households at the bottom of the income distribution are impacted more by the carbon tax (Annex Figure 3.7.2). These households are affected by both the increase in energy prices and a reduction in wages. Unskilled workers' wages fall more than the wages of skilled workers. The skill premium increases because the carbon tax reduces the high-energy intensive goods’ demand and unskilled workers work disproportionately more in this sector.

When the revenue is used to finance a cash-transfer program instead of government spending, consumption of unskilled households goes up (Annex Figure 3.7.2), reducing income inequality to levels below the baseline, and this reduction is more considerable when the transfers are targeted to the bottom two quintiles of the income distribution.

Annex Figure 3.7.2. Distributional Impact of Carbon Taxes
(Percent of household total consumption expenditure)



Source: IMF staff calculations.
Note: Panels 1 and 2 show the result of the multisector heterogeneous agent model simulation of a $50 tax per ton of carbon dioxide, where the revenue is used to finance government spending on (1) low-energy-intensive goods, (2) universal cash-transfers, and (3) targeted cash-transfers to the bottom two quintiles of the income distribution, and (4) a subsidy to the consumption of clean energy. In panels 1 and 2, each bar shows the percentage change in consumption with respect to the baseline, in a model calibrated to the United States (Panel 1), and in a model calibrated to China (Panel 2). Q = quintile, where Q1 = bottom quintile and Q5 = top quintile.

Feebates are another tool that governments use to fight climate change. Feebates can be targeted to specific markets, and their impact on emissions depends on the size of the market and its energy intensity. This section considers a feebate scheme under which the revenue from the carbon tax is used to subsidize clean energy consumption. The feebate impacts the price of energy and high-energy intensive goods relative to low-energy intensive-good less than in the case of a pure carbon tax scheme because of the subsidy to clean energy. This mitigates the effects on the consumption of households at the bottom of the income distribution. In addition, because the revenue is used to subsidize clean energy consumption, and the production of clean energy is more intensive in unskilled labor than the production of dirty energy, feebates boost labor demand for unskilled workers. This boost in demand mitigates the carbon tax impact on the skill premium, reducing income inequality (Annex Table 3.7.1).

Annex Table 3.7.1. The Distributional Impact of Carbon Tax and Mitigation Measures

(Percent change)

	Low-energy government spending	Universal cash-transfers	Targeted cash-transfers	Feebates
United States				
Gini coefficient	0.35	-1.35	-2.24	-0.28
Skill premium	1.72	1.1	0.14	-0.41
China				
Gini coefficient	0.12	-3.81	-4.52	-0.27
Skill premium	2.52	1.53	0.24	-1.51

Source: IMF staff calculations.

Note: The Table shows the result of the multi-sector heterogeneous agent model simulation of a 50 US dollar per tCO_2 tax on carbon where the revenue is used to finance government spending on (1) low-energy intensive goods, (2) universal cash-transfers, (3) targeted cash-transfers to the bottom two quintiles of the income distribution, and (4) a subsidy to the consumption of clean energy. The table shows the percentage change with respect to the baseline of the Gini coefficient and the skill premium, measured as the ratio of wages of workers with more than high school education (skilled) over the wages of workers with at most high school education (unskilled).