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Climate Change Mitigation Policies: Aggregate and Distributional Effects

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March 7, 2021

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We evaluate the aggregate and distributional effects of climate change mitigation policies using a multi-sector equilibrium model with intersectoral input–output linkages and worker heterogeneity calibrated to different countries. The introduction of carbon taxes leads to changes in relative prices and inputs reallocation, including labor. For the United States, reaching its original Paris Agreement pledge would imply at most a 0.6% drop in output. This impact is distributed asymmetrically across sectors and individuals. In the US, workers with a comparative advantage in dirty energy sectors who do not reallocate suffer a welfare loss 12 times higher than workers in non-dirty sectors, but constitute less than 1% of the labor force.

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1 Introduction

As greenhouse gas emissions reach alarming levels, there is increasing pressure on countries to adopt more aggressive environmental policies. However, concerns regarding their economic and distributional effects hinder the adoption of these policies, as reducing emissions means reallocating resources away from high-carbon sectors towards low-carbon ones. A clear example of such tension is the United States, where the Trump administration dropped out of the Paris Agreement Accord and President Biden just recently returned. This paper investigates the aggregate and distributional effects of climate change mitigation policies, by focusing on the reallocation of inputs, and labor in particular, across the different sectors of the economy.

We develop a framework that integrates the workers' skill distribution with the economy's sectoral composition. The theory builds on the Roy model of occupational choice with endogenous human capital investment, in which workers choose sectors based on relative wages and their comparative advantage (Roy, 1951; Hsieh et al., 2019). The model economy consists of various sectors, including four energy-producing activities: oil, coal, natural gas and green. A carbon tax is introduced to the "dirty" energy producers, which in turn affects their prices.[1] Given the intersectoral linkages in the economy, these changes in relative prices create substitution possibilities between all inputs of production, which lead to labor reallocation across sectors. The overall economic impact depends on the magnitude of the tax and on how the revenue is rebated to the economy. As economies differ in their production structures and labor force characteristics, the impact of carbon taxes is likely to vary across countries. We thus calibrate the model parameters for the following six countries: Brazil, Canada, China, India, Mexico and the United States.

We investigate the economic impact of introducing a 32.3% carbon tax, which is the estimated tax needed for the United States to achieve its original Paris Agreement pledge of a 26% reduction in emissions (Ramstein

[1]The "dirty energy sectors" hereafter refer to oil, coal and natural gas sectors. "Non-dirty energy sector" refers to the green sector.

et al., 2019). This carbon tax costs the United States at most a 0.6% drop in output. We then implement the same tax policy for the remaining five countries in order to capture the heterogeneity in responses among these economies. We show that, in the worst case scenario, a 32.3% carbon tax can cause a GDP loss ranging from 0.5% (for Brazil) to 2.1% (for China). However, this drop in GDP can be partially offset by implementing tax rebates.

The relatively small aggregate effects mask sizable heterogeneity at the sectoral and individual levels, where there are non-trivial distributional effects. Our results show that dirty energy sectors exposed to the carbon tax witness the largest drop in wages, and consequently the largest labor outflow. By examining the skill distribution, we show that marginal (relatively less-talented) workers in dirty energy production choose to reallocate away from the taxed sectors. Workers with a strong comparative advantage in the dirty energy production remain working in this sector and end up bearing the cost of the drop in wages. In the US, the welfare loss for this group is 12 times higher than for workers who work in non-dirty sectors. Nevertheless, these workers constitute a small fraction of the labor force; less than 0.6% in the US.

An important research agenda has concentrated on finding the optimal level of carbon taxation by integrating the climate and the economy into a single model, as proposed by Nordhaus (1994); Dietz and Stern (2015); Golosov et al. (2014); Hassler et al. (2018); Tol (2018). Their findings point to the effectiveness of carbon taxes in curbing greenhouse gas emissions and reducing emission-induced economic damage. However, this research abstracts from the distributional impacts of climate change mitigation policies, which is a key feature of our analysis.

There is a related literature investigating the distributional effects of carbon taxation. Grainger and Kolstad (2010), for instance, find that carbon taxes tend to be regressive by focusing on the use-side incidence of such taxes, since lower-income households devote a larger share of their expenditures to energy consumption. However, other papers show that carbon taxes can have progressive impacts once the source-side, i.e. the relative change in remuneration of factor inputs, is taken into account and tax revenues are rebated (e.g., Dissou and Siddiqui (2014); Goulder et al. (2019); Tavares (2020); Chateau et al. (2018); Bosetti and Maffezzoli (2013)). Our paper investigates the aggregate and distributional effects of carbon taxes by exploring how changes in factor prices induced by carbon taxes cascade to the rest of the economy and lead to sectoral reallocation of inputs, including labor.[2] Unlike previous studies investigating the source-side impacts of carbon taxes, individuals in our framework are heterogeneous in their ability to work in different economic activities and choose their human capital investment based on their comparative advantage and the human capital return in such occupation.

The rest of this paper is structured as follows. Section 2 describes the model and characterizes its equilibrium. Section 3 discusses the calibration strategy. Section 4 presents the aggregate results and Section 5 the sectoral- and individual-level results of the counterfactual analyses. Section 6 concludes.

2 The Model

The model economy consists of individuals who live for two periods. As in Hsieh et al. (2019), in the first period of life, workers draw an ability vector that determines their productivity[3] for working in each sector of the economy. They make their occupational choice and invest in human capital. In the second period, individuals work and consume. On the production side, each sector produces a distinct intermediate good, including four types of energy: oil, coal, natural gas and green. There is also a final good sector. We describe the details of the model environment below.

[2]There are some papers studying the effects of climate policies on jobs by considering the unemployment dimension (e.g., Aubert and Chiroleu-Assouline (2019); Castellanos and Heutel (2019); Hafstead and Williams III (2018)). They are related to the literature covering the labor market dimension of non-climate policies such as trade and innovation policies. See, for instance, Adão et al. (2020); David et al. (2013); Lyon and Waugh (2019).

[3]Ability, talent, comparative advantage, and productivity are used interchangeably.

2.1 Households

There is a continuum of measure one of individuals, each working in one of the J intermediate sectors. Individuals have two units of time: one unit when they are "young", which is allocated between leisure and schooling; and one unit when they are "old", when they supply their labor inelastically to one of the intermediate goods sectors.

Each individual derives utility from consumption, c, and leisure, $(1-s)$, according to the following utility function:[4]

$$U = c^{\gamma}(1-s),\ \gamma > 0,$$

where s denotes time spent on schooling in the first period of life and γ controls the relative weight of consumption in the individual's utility.

Human capital for sector j depends on schooling time, s, and schooling resources (like books or tuition fees), e, and is given by:

$$h(s,e) = s^{\phi_j} e^{\eta}.$$

The elasticity of human capital with respect to time is sector-specific, ϕ_j, such that different sectors feature different returns to schooling.

The individual's labor income is the product of the wage per efficiency unit in sector j, w_j, their idiosyncratic ability draw, z_j, and their acquired human capital for sector j, $h(s,e)$. Individual income is split between consumption, c, and expenditures on schooling resources, e. Given an occupational choice, wage, and idiosyncratic talent, z_j, the individual's utility maximization problem is given by:

$$U_j(w_j, z_j) = \max_{c,s,e} c^{\gamma}(1-s) \ \text{ subject to } \ c = w_j z_j h(s,e) - e. \tag{1}$$

[4]To save on notation, individuals will not be indexed by a superscript.

The equations describing the solution of this problem are:

$$s_j^* = \frac{1}{1 + \frac{1-\eta}{\gamma\phi_j}}, \tag{2}$$

$$e_j^*(z_j) = \left(\eta w_j z_j (s_j^*)^{\phi_j}\right)^{\frac{1}{1-\eta}} . \tag{3}$$

Note that changes in wages do not affect the individual choices of time spent on schooling ($\partial s_j^*/\partial w_j = 0$), but do affect the amount of goods spent on schooling resources ($\partial e_j^*/\partial w_j > 0$).

After substituting equations (2) and (3) into (1), the individual's indirect utility reads:

$$U_j^* = \left[w_j z_j s_j^{\phi_j} (1 - s_j)^{\frac{1-\eta}{\beta}} \eta^\eta (1-\eta)^{(1-\eta)}\right]^{\frac{\beta}{1-\eta}} . \tag{4}$$

2.1.1 Occupational Skills

Each worker is endowed with a vector of idiosyncratic abilities $\{z_j\}_{j=1}^J$. We assume that the individual's abilities for the J sectors are drawn from a multivariate Fréchet distribution, such that:

$$F(z_1, ..., z_J) = \exp\left(-\sum_{j=1}^{J} (z_j)^{-\lambda}\right), \ \lambda > 1,$$

where the parameter λ measures the dispersion of individual productivity across sectors. A higher value of λ corresponds to smaller dispersion. When λ is small, workers' abilities are more dispersed, and hence a larger change in wages is needed to get workers to reallocate across sectors. And vice versa.

2.1.2 Occupational Choice

Self-selection is driven by how heterogeneous abilities interact with the endogenous components of an individual's utility in (4). Workers supply their labor to the sector which offers them the highest relative returns given their vector of ability, i.e. highest utility $\max_j\{U_j\}$.

Knowing the decision rule behind workers' occupational choice, we can calculate the share of workers in each of the sectors of the economy.

Proposition 1 *The share of workers in sector j, denoted by q_j, is given by:*

$$q_j = \frac{\tilde{w}_j^{\lambda}}{\sum_k \tilde{w}_k^{\lambda}} \text{ where } \tilde{w}_j = w_j s_j^{\phi_j} (1 - s_j)^{\frac{1-\eta}{\beta}} \text{ for } j \in \{1, ..., J\}. \tag{5}$$

Proof: See Appendix A.1. ■

Each worker's occupation choice is driven by *relative* returns $\tilde{w}_j z_j$ instead of *absolute* returns $\tilde{w}_j$. Using the tractability afforded by the Fréchet distribution, we can write the share of workers in each sector using (5). Having calculated the labor supply for each sector, we can now compute the efficiency units of labor supplied (i.e. effective labor supply) in each sector.

Proposition 2 *The effective labor supply for sector j is given by:*

$$L_j^s = (s_j^{\phi_j})^{\frac{1}{1-\eta}} (\eta w_j)^{\frac{\eta}{1-\eta}} q_j^{1-\frac{1}{\lambda}\frac{1}{1-\eta}} \Gamma\left(1 - \frac{1}{\lambda}\frac{1}{1-\eta}\right) \text{ for } j \in \{1, ..., J\}, \tag{6}$$

where $\Gamma\left(1 - \frac{1}{\lambda}\frac{1}{1-\eta}\right)$ is the Gamma function evaluated at the constant $\frac{1}{\lambda}\frac{1}{1-\eta}$.

Proof: See Appendix A.2. ■

Using equations (5) and (6), we can calculate average worker quality in a sector by taking the ratio of efficiency units of labor supplied over the units of labor supplied, L_j^s/q_j. Average quality is therefore inversely related to the labor share in each sector, which captures a selection effect.

2.2 Production

Recall that there are J intermediate good sectors and one final good sector. We will now describe each of these in turn.

2.2.1 Intermediate Goods

Our production setup is similar to trade models such as Eaton and Kortum (2002). There are J sectors, each producing a differentiated intermediate good. Among these, there are four energy sectors: oil, coal, natural gas, and green. The first three energy sectors are polluting, so we will refer to them as the "dirty" energy sectors, and the fourth sector is the "clean" energy sector. The technology to produce each intermediate good $j \in \{1, 2, ..., J\}$ is represented by a Cobb-Douglas function with constant returns to scale:

$$Y_j = L_j^{\beta_j} \prod_{k=1}^{J} x_{jk}^{\nu_{jk}}, \ \beta_j, \nu_{jk} \in [0,1]; \ and \ \beta_j + \sum_{k=1}^{J} \nu_{jk} = 1,$$

where L_j corresponds to effective labor input and β_j is the labor share in sector j. The variable x_{jk} denotes the quantity of good k used in the production of good j. The parameter ν_{jk} determines the relative importance of good k in the production of sector j.[5] The inclusion of intersectoral linkages allows for a more detailed analysis of the general equilibrium effects of adding a carbon tax (Jones, 2011; Acemoglu et al., 2012; King et al., 2019).

The representative firm in the intermediate good sector j chooses labor L_j and intermediate inputs $\{x_{jk}\}_{k=1}^{J}$ to maximize:

$$\pi_j = \max_{L_j, x_{jk}} \Big\{ P_j L_j^{\beta_j} \prod_{k=1}^{J} x_{jk}^{\nu_{jk}} - w_j L_j - \sum_{k=1}^{J} P_k x_{jk} \Big\}, \tag{7}$$

where P_j is the price of intermediate good j and w_j is the wage rate paid in sector j. Inputs are paid according to their marginal products, such that:

$$\beta_j P_j L_j^{\beta_j - 1} \prod_{k=1}^{J} x_{jk}^{\nu_{jk}} = w_j,$$

[5] Golosov et al. (2014) estimated the elasticity of substitution between dirty and clean energy sources to be 0.95 based on a metastudy of 47 studies of interfuel substitution (Stern, 2012). Therefore, the unitary elasticity of substitution assumed here seems a reasonable simplification.

$$\nu_{jk} P_j L_j^{\beta_j} x_{jk}^{\nu_{jk}-1} \prod_{k \neq s} x_{js}^{\nu_{js}} = P_k, \ \forall x_{jk}, \ k \in \{1, 2, ..., J\}.$$

2.2.2 Final Good

The technology for the final good, Y_f, is given by a production function that uses differentiated intermediate goods $\{Y_j^F\}_{j=1}^J$ according to the following aggregator:

$$Y_f = \prod_{j=1} \left(Y_j^F\right)^{\sigma_j}, \ \sigma_j \in [0,1) \text{ and } \sum_{j=1}^{J} \sigma_j = 1.$$

The final good is the numéraire, such that its price P_f is normalized to 1. The optimization problem of the representative firm in the final good sector is to choose each input $\{Y_j^F\}_{j=1}^J$ to maximize:

$$\pi_f = \max_{Y_j} \left\{ \prod_{j=1} \left(Y_j^F\right)^{\sigma_j} - \sum_j P_j Y_j^F \right\}, \tag{8}$$

and the optimal demand for each input satisfies:

$$Y_j^F = \sigma_j \frac{Y_f}{P_j}, \ \forall j \in \{1, 2, ..., J\}.$$

2.3 Equilibrium

The stationary competitive equilibrium for this economy consists of individual choices $\{c, s, e\}$, individual occupational choices, efficiency units of labor input in each sector $\{L_j\}_{j=1}^J$, intermediate goods $\{Y_j\}_{j=1}^J$, final output Y_f, wages $\{w_j\}_{j=1}^J$ and prices of intermediate goods $\{P_j\}_{j=1}^J$, such that:

- Individuals maximize their utility, according to equation (1).
- Individuals supply their labor to the sector that provides them with the highest income according to their abilities.
- Firms producing intermediate goods maximize profits, according to equation (7).

- The representative firm of the final good maximizes profits, according to equation (8).

- All markets clear.

2.4 Carbon Taxation

A carbon tax affects the prices of energy inputs, particularly the more polluting types. Therefore, the burden of the tax on the price of each energy type should depend on the carbon content of that particular energy type. Following Golosov et al. (2014) and Hassler et al. (2018), we differentiate between four energy inputs (oil, coal, natural gas and green) according to their carbon content (intensity of carbon emissions to the atmosphere). Denote this content by g_j, such that $g_j \in [0, 1]$. Green energy types (such as wind and solar) are not associated with any climate externality, so $g_{green} = 0$. The carbon tax rate on each energy type is given by $\tau_j = \tau g_j \; \forall j$ (note that $\tau_{green} = 0$ since $g_{green} = 0$).

We introduce the carbon tax as a sales tax to each energy type j, such that profits in energy type j, in the presence of such a tax, are given by:

$$\pi_j = (1 - \tau_j) P_j Y_j - w_j L_j - \sum_{k=1}^{J} P_k x_{jk}.$$

In our simulations, we consider different ways to allocate revenues raised with carbon taxes and adjust the equilibrium conditions accordingly. For instance, in one counterfactual experiment, we consider the use of tax revenues in dirty energy sectors to subsidize the green energy sector. In that experiment, the green subsidy is designed such that the carbon tax is revenue neutral (i.e. $\sum_{j=1}^{J} \tau_j P_j Y_j = 0$), which implies that $\tau_{green} < 0$.

3 Calibration

This section discusses how we discipline the model parameters in order to investigate the aggregate and distributional effects of climate change mitigation policies. Since these effects are likely to vary across countries due to country-specific characteristics (e.g. production structure and labor force composition), the parameterization of the model is conducted by disciplining the parameters with micro-level data for a sample of six countries spanning a set of developing and advanced economies, namely: Brazil, Canada, China, India, Mexico and United States. We have prior information about some model parameters, such as the importance of each input in the production of intermediate goods. But other parameters are specific to the analysis and we do not have much information about their magnitude. They will be internally estimated to match key moments of the data. Table B1 in the Appendix lists all the model parameters and divides them into these two groups.

External Calibration. To set values for J, β_j, and ν_{jk}, we use data from the World Input Output Database (WIOD), which contains national input-output tables, as well as data on sectoral labor force participation rates, labor compensation, and environmental accounts for the countries in our sample. We use data on inter-sectoral sales to calculate ν_{jk} and set $\beta_j = 1 - \sum_{k=1}^{J} \nu_{jk}$. We aggregate the 35 sectors in the WIOD into 15 sectors including one aggregate energy sector (see Table B2 in the Appendix). We then split the aggregate energy sector into oil, coal, natural gas and green energy production based on the energy input mix of each of the intermediate sectors, according to the WIOD environmental accounts on energy use by sector and energy type. We also use the WIOD environmental accounts data on CO_2 emissions by sector and energy type to calculate the effect of taxes on emissions.[6] More details on these parameters are presented in Appendix B.

The sectoral carbon content, g_j, is based on Golosov et al. (2014). The numbers for oil and coal are $g_{oil} = 0.846$ and $g_{coal} = 0.716$. We replicate their methodology and calculate $g_{gas} = 0.734$ using estimates from Garg et al. (2006).

We follow Hsieh et al. (2019) to calibrate η and γ. η is equal to the fraction

[6]Note that our framework does not model the feedback effects of emissions on the economy. We compute the change in emissions in order to discipline the size of the carbon tax.

of output spent on education. From the World Development Indicators (WDI), we collect the most recent data on public expenditure on education (as a share of GDP) and normalize it by labor force participation rate to calculate η for each country.[7] To calibrate γ, we take average earnings in sector j, $\bar{w}_j = w_j\,\mathbb{E}[hz_j] = (1-s)^{\frac{-1}{\gamma}}\eta^{\frac{\eta}{1-\eta}}\Gamma(1-\frac{1}{\lambda}\frac{1}{1-\eta})$. Note that average earnings is proportional to $(1-s)^{\frac{-1}{\gamma}}$. We use micro-data from the Integrated Public Use Micro-data Series (IPUMS) for each country in our sample, except China.[8] We then calculate the average years of schooling divided by a pre-work time endowment of 25 years, $\bar{s}$, and estimate the Mincerian return to schooling across sectors, ξ, from a regression of log average wages on average schooling across sectors for each country. With $\bar{s}$ and ξ, we calculate $\gamma = \frac{1}{\xi(1-\bar{s})}$. The values for η and γ for each country are presented in Tables B3 and B5 in the Appendix, respectively.

Internal Calibration. The remaining parameters σ_j, ϕ_j and λ are disciplined by solving the model and targeting certain data moments. In particular, we calibrate the expenditure shares σ_j such that the sectoral value added shares in the model match those in the data.

We follow the methodology in Hsieh et al. (2019) to estimate ϕ_j and λ. To estimate ϕ_j, we use data from WIOD on the number of employees and labor compensation to calculate the average wage in each sector.[9] This yields the relative sectoral wages, which determine the relative values for ϕ_j. To find the absolute values of ϕ_j, we take the ratio of the average wages relative to Agriculture. We calculate average schooling in agriculture s_{Agri} and then use equation (2) to solve for ϕ_{Agri}. With this, we pin down the remaining ϕ_j by targeting the ratio of each sectoral wage relative to Agriculture.[10] Data on the relative ratios of sectoral wages and the values for ϕ for each country are presented in Table B6 in the Appendix.

[7]Two remarks: (i) we obtain expenditure on education for China from the Ministry of Finance for the People's Republic of China. (ii) we re-estimate η using data on public and private expenditure on education from OECD for Brazil, Canada, Mexico and United States. The results were similar and are available upon request.

[8]For China, we use micro-data from the Chinese Household Income Project, 2013.

[9]For China, data on number of employees is not available; so we use data on the number of people engaged instead.

[10]Given the lack of information on the individual energy sectors, we target the ratio of average wage in the aggregate energy sector relative to agriculture.

To estimate λ, we use micro-data on individual wages to fit the distribution of residuals from a cross-sectional regression of log income earned on age-industry dummies in a given year for each country. We then match the coefficient of variation of sectoral residual wages. The values of estimated Fréchet parameters, alongside data and model's estimates of the coefficient of variation of wages for each country are presented in Table B7 in the Appendix.

Model Fit. Following the calibration strategy above, we target sectoral value added shares, ratios of relative wages, and the coefficient of variation of wages. Although labor force participation rates are not targeted, the model's estimates of sectoral labor force participation shares are highly correlated to their data counterparts (with an average correlation of 0.80 across countries); see Table B8 in the Appendix. To target labor force participation shares exactly, we add wedges to the wages to capture pre-existing distortions in the labor market in the benchmark model. We run this robustness check for the case of Mexico, which has the worst fit for untargeted labor force participation rates, and show that the main results hold upon adding such wedges; see Appendix D.

4 The Aggregate Effects of Climate Change Mitigation Policies

To investigate how the economy reacts to climate change mitigation policies, we introduce a carbon tax on the "dirty" energy sectors. We consider five different counterfactual policies in which tax revenue is either: (i) wastefully spent, i.e. not rebated back ("Wasteful Spending"); (ii) used to subsidize green energy ("Green Subsidy"); (iii) used to subsidize all non-dirty sectors in the economy ("Useful Spending"); (iv) used to subsidize education expenditures for all non-dirty sectors ("Education Subsidy"); or (v) rebated back to households uniformly as lump sum transfers ("Household Transfers").[11]

[11] In policies (ii)-(v), subsidies are designed such that the government budget is balanced.

Similar to King et al. (2019), our model does not feature an externality since emissions do not affect production or consumption. Hence, given the absence of externalities, the optimal carbon tax is zero in the benchmark model. Our goal is not to investigate the optimal policy but to understand the aggregate and distributional effects of imposing a carbon tax aimed at reducing emissions. Therefore, our exercises are positive rather than normative.

More specifically, our experiments increase the tax rate on oil, coal and gas energy production sectors from $\tau = 0\%$ to $\tau = 32.3\%$.[12] This is the tax rate needed for the United States to achieve its original Paris Agreement pledge to reduce total emissions by 26% (Ramstein et al., 2019). We also apply the 32.3% carbon tax to five different advanced and emerging economies: Brazil, Canada, China, India and Mexico. Investigating countries with different levels of development and production structures allows us to capture heterogeneous responses across countries to the same climate change mitigation policy.

Table 1 displays the main aggregate results for this analysis. Panel A reports the results on emissions, GDP, consumption and welfare of introducing a 32.3% carbon tax in the six countries analyzed. For each country, these results are presented for the different types of tax rebates. Take the United States, for instance. By construction, in the wasteful spending scenario, the tax leads to a 26% reduction in total emissions. Since the dirty energy sectors pollute more than the other activities, the drop in fossil emissions is larger (26.8%). As energy becomes more expensive, the economy contracts and GDP falls by 0.6%. With the tax, reallocation of resources and fall in output, aggregate welfare decreases.

If the government uses the carbon tax revenue to subsidize the green sector, the fall in GDP is dampened to only 0.3%. With more economic activity, emissions actually decline by less than with wasteful spending even with subsidies to the clean sector. An alternative is to subsidize all non-dirty

[12] Adding a 32.3% value added tax translates into a tax $\tau_{oil} = 27.3\%$ on oil sales, $\tau_{coal} = 23.1\%$ on coal sales, and $\tau_{gas} = 23.7\%$ on gas sales upon adjusting for the carbon content of each energy input. This tax rate is equivalent to 37.7 US$ per ton of CO_2 in the United States.

sectors (Useful Spending). Again, the fall in GDP is dampened relative to the wasteful scenario, but emissions do not fall by as much.

When tax revenues are used to finance education subsidies, US GDP rises by 0.4%. Individuals invest more in education with this policy, increasing individual productivity and therefore aggregate output. Moreover, the education subsidy partially insures individuals, and this can lead to an increase in welfare. This type of insurance coupled with a hike in leisure also explains why welfare increases substantially in the household transfer scenario even though GDP declines. However, given the implausibility of lump-sum transfers in the real world, we do not focus on household transfer results for the remainder of the analysis.

Panel A of Table 1 also displays the results for the other five countries in our sample. The main insights across the different types of tax rebates found for the United States carry over to the other countries. The main differences are on the magnitude of the effects. The reduction in total emissions ranges from 24.0% in Canada to 32.1% in China. With regards to GDP, the losses for the wasteful spending counterfactual range from 0.5% in Brazil to 2.1% in China. The amplitude for the other scenarios is comparable. Two key messages from our results stand out. First, the carbon tax has heterogeneous aggregate effects amongst these six countries. This hinges on the varying importance of the taxed sectors in each country's total value added, intermediate consumption and/or labor force composition. Second, a 32.3% carbon tax seems to have relatively small aggregate output effects. This happens because the dirty energy sectors constitute a small fraction of the gross output in each economy. More detailed results are reported in Tables C10 and C11 in the Appendix.

4.1 China versus the United States

Panel A in Table 1 reported the results for a 32.3% carbon tax, which is needed for the United States to achieve its original Paris Agreement goal. Such a policy yields different effects across countries. Instead of applying the same climate policy for all countries, this subsection solves for the tax

Table 1: The Effects of Climate Change Mitigation Policy Under All Recycling Schemes

Panel A: 32.3% Carbon Tax					
Brazil	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-25.9	-27.5	-0.5	-1.4	-0.9
Green Subsidy	-25.0	-26.5	-0.2	-0.2	-0.2
Useful Spending	-25.5	-27.1	-0.4	-0.4	0.1
Education Subsidy	-25.9	-27.5	0.4	-0.5	0.1
Household Transfers	-25.9	-27.5	-1.1	-1.0	1.3
Canada	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-24.0	-26.6	-1.2	-3.9	-2.9
Green Subsidy	-22.9	-25.5	-0.8	-0.8	-0.9
Useful Spending	-22.8	-25.4	-1.1	-1.1	0.2
Education Subsidy	-24.0	-26.6	1.2	-1.6	-0.3
Household Transfers	-24.0	-26.6	-3.1	-2.9	2.5
China	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-32.1	-34.0	-2.1	-6.0	-4.7
Green Subsidy	-25.9	-27.5	-1.2	-1.2	-1.9
Useful Spending	-29.1	-31.0	-1.9	-1.9	-0.4
Education Subsidy	-32.1	-34.0	0.9	-3.1	-1.7
Household Transfers	-32.1	-34.0	-4.5	-4.3	2.8
India	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-28.2	-29.9	-1.0	-2.9	-2.1
Green Subsidy	-25.4	-26.9	-0.5	-0.5	-0.7
Useful Spending	-26.7	-28.3	-0.8	-0.8	0.0
Education Subsidy	-28.2	-29.9	0.7	-1.2	-0.2
Household Transfers	-28.2	-29.9	-2.7	-2.5	2.5
Mexico	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-25.3	-26.8	-1.1	-3.4	-2.2
Green Subsidy	-24.6	-26.1	-0.7	-0.7	-0.8
Useful Spending	-24.2	-25.7	-1.0	-1.0	0.4
Education Subsidy	-25.3	-26.8	1.0	-1.4	0.0
Household Transfers	-25.3	-26.8	-3.0	-2.8	2.7
United States	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-26.0	-26.8	-0.6	-1.7	-1.1
Green Subsidy	-24.3	-25.0	-0.3	-0.3	-0.3
Useful Spending	-25.3	-26.1	-0.5	-0.5	0.1
Education Subsidy	-26.0	-26.8	0.4	-0.7	0.1
Household Transfers	-26.0	-26.8	-1.9	-1.8	1.1
Panel B: 25.4% Carbon Tax					
China	Total Emissions	Fossil Emissions	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-26.0	-27.5	-1.5	-4.7	-3.6
Green Subsidy	-20.6	-21.8	-0.7	-0.7	-1.2
Useful Spending	-23.4	-24.8	-1.3	-1.3	-0.1
Education Subsidy	-26.0	-27.5	1.0	-2.2	-1.0
Household Transfers	-26.0	-27.5	-3.5	-3.3	2.5

rate needed for a country to achieve the same climate target as the United States; i.e. a reduction in emissions of 26%. We take China as an example and find that it requires a carbon tax of 25.4% to achieve such a reduction in emissions. Panel B of Table 1 reports the results for this counterfactual.

A similar reduction in emissions in the United States and China generates larger aggregate output effects in China. For the wasteful spending case, the same reduction in emissions leads to a fall in GDP of 0.6% and 1.5% in the United States and China, respectively. This is due to the fact that China is more reliant on dirty energy than the United States. China has a higher share of oil, coal and natural gas in its intermediate consumption (5.4% vs. 1.8%), value added (4.4% vs. 3.0%) and labor force composition (1.9% vs. 0.6%) compared with the United States. See Table C11 for more details.

5 The Distributional Effects of Climate Change Mitigation Policies

The previous section highlighted the relatively small aggregate losses caused by the introduction of a carbon tax. This section investigates the sectoral- and individual-level effects of this policy.

5.1 Sectoral-level Analysis

Introducing the carbon tax on oil, coal and natural gas energy sectors causes them to downsize as they become more expensive relative to other sectors. As a result, labor demand and wages in these sectors fall. Workers re-optimize their occupational decisions and some switch sectors. Figure 1 shows the changes in equilibrium labor by sectors. Employment in the oil, coal and natural gas sectors drops, while it increases in the non-dirty sectors of the economy. With the subsidy to clean energy, inputs are reallocated from the dirty energy sectors to the green sector to equalize marginal returns. With an education subsidy, human capital rises because education

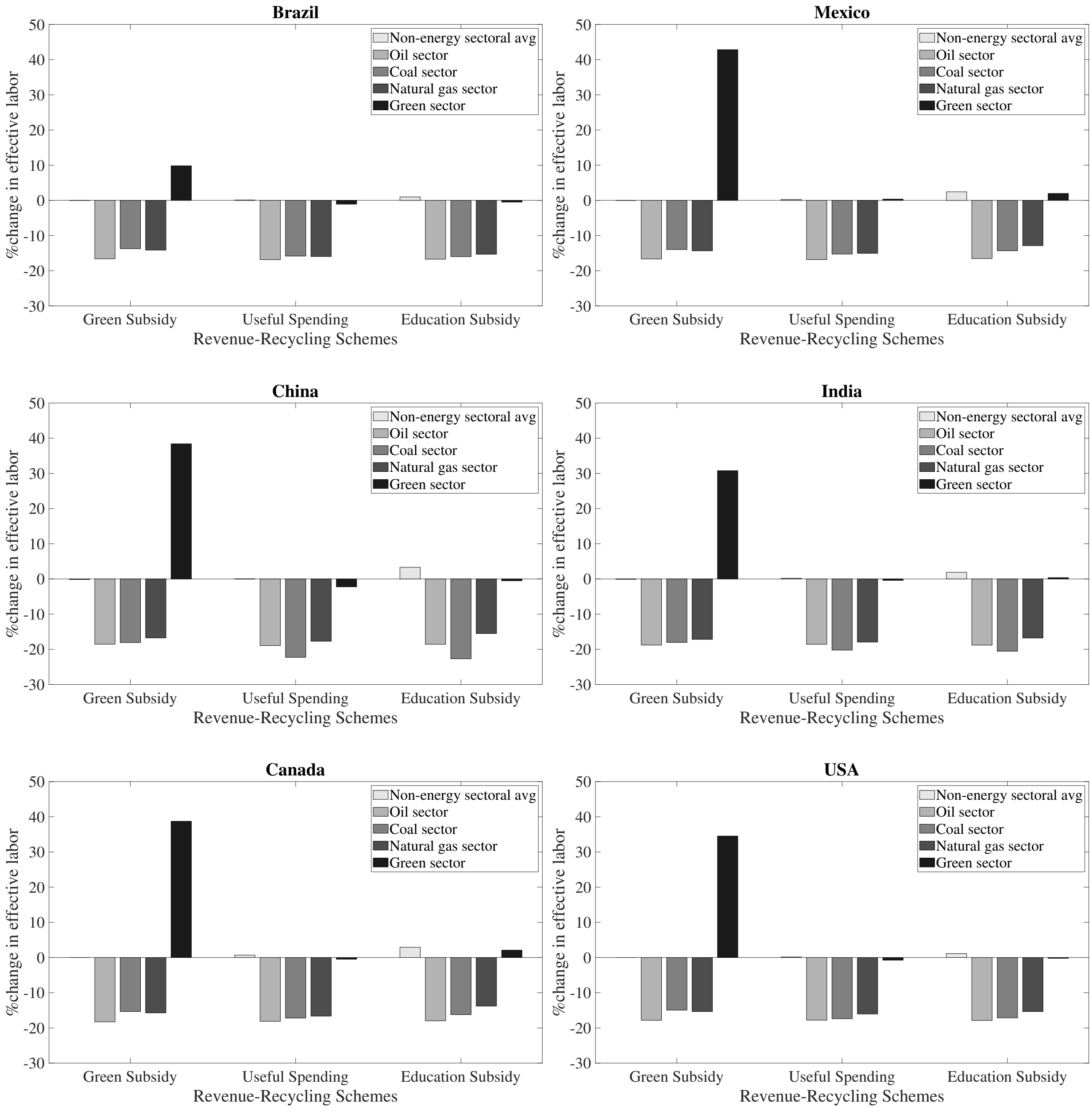

Figure 1: Percentage Change in Effective Labor Upon Increasing Carbon Tax from 0% (benchmark) to 32.3% Across All Scenarios.

becomes relatively cheaper, reinforcing the increase in effective labor to the sectors not directly affected by the carbon tax.

The occupational decision of workers is driven by their innate abilities and the wage in each occupation. Marginal workers with relatively low productivity in the dirty energy sectors reallocate to other sectors of the economy. Workers with a high comparative advantage in the dirty energy sectors remain in these sectors after the policy change. Therefore, due to a selection effect, the average productivity of workers in the taxed sectors rises (see Figure 2). In the green subsidy scenario, average productivity drops significantly in the green sector due to the inflow of workers to this sector, as depicted in Figure 1.

5.2 Individual-level Analysis

We now investigate the distributional effects more closely by focusing on individual-level effects that arise after the introduction of a carbon tax. We split workers into four categories: (i) those who remain in the non-dirty energy sectors; (ii) those who reallocate from non-dirty energy sectors; (iii) those who remain in dirty energy sectors; and (iv) those who reallocate from dirty energy sectors. We then track how their welfare changes after the implementation of the policy. Welfare is measured by the consumption equivalent variation from adding the carbon tax relative to the baseline.

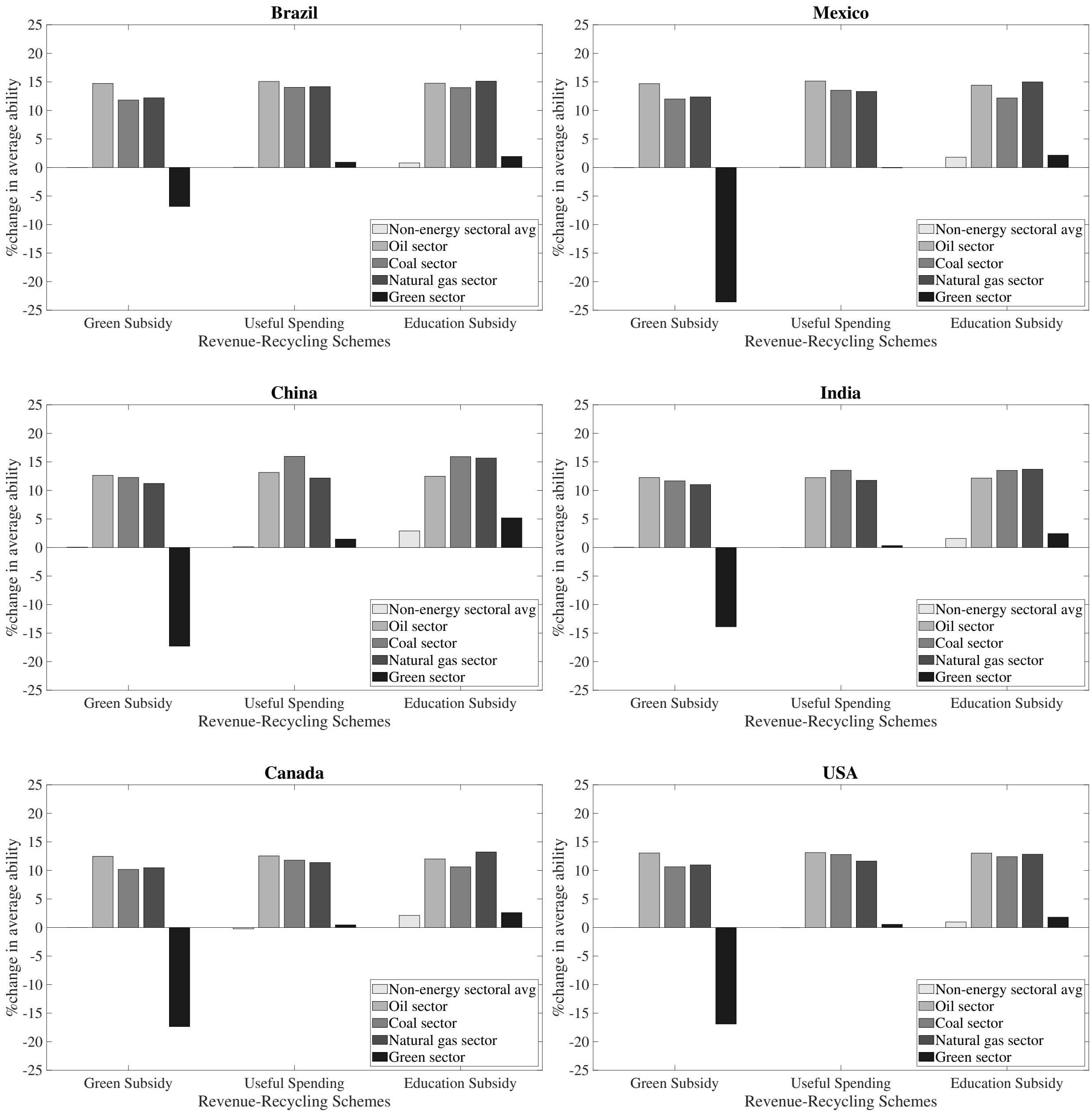

Figure 2: Percentage Change in Average Productivity Upon Increasing Carbon Tax from 0% (benchmark) to 32.3% Across All Scenarios.

Table 2: Detailed Welfare Analysis by Country

Brazil	Wasteful Spending		Green Subsidy		Useful Spending		Education Subsidy	
	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)
Non-dirty sectors, stayers	-0.9	99.6	0.4	99.7	0.1	99.7	0.1	99.6
Non-dirty sectors, switchers	-0.9	0.1	2.8	0.1	0.2	0.1	0.1	0.1
Dirty sectors, stayers	-14.6	0.2	-12.7	0.2	-13.7	0.2	-13.7	0.2
Dirty sectors, switchers	-7.7	0.1	-6.5	0.1	-6.8	0.1	-6.8	0.1
Aggregate	-0.9	100.0	-0.2	100.0	0.1	100.0	0.1	100.0
Canada	Wasteful Spending		Green Subsidy		Useful Spending		Education Subsidy	
	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)
Non-dirty sectors, stayers	-2.6	96.9	0.6	96.4	0.5	96.9	0.0	96.9
Non-dirty sectors, switchers	-2.5	0.2	9.1	0.7	0.5	0.2	0.1	0.2
Dirty sectors, stayers	-13.4	2.1	-11.6	2.1	-11.3	2.1	-11.2	2.1
Dirty sectors, switchers	-7.8	0.7	-5.6	0.8	-5.2	0.8	-5.4	0.7
Aggregate	-2.9	100.0	-0.9	100.0	0.2	100.0	-0.3	100.0
China	Wasteful Spending		Green Subsidy		Useful Spending		Education Subsidy	
	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)
Non-dirty sectors, stayers	-4.7	98.2	-0.5	98.0	-0.6	98.4	-1.7	98.2
Non-dirty sectors, switchers	-4.5	0.4	6.0	0.7	-0.4	0.3	-1.4	0.4
Dirty sectors, stayers	-16.7	0.9	-13.0	1.0	-13.0	0.9	-14.1	0.9
Dirty sectors, switchers	-10.4	0.4	-6.9	0.4	-6.4	0.4	-7.5	0.4
Aggregate	-4.7	100.0	-1.9	100.0	-0.4	100.0	-1.7	100.0
India	Wasteful Spending		Green Subsidy		Useful Spending		Education Subsidy	
	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)
Non-dirty sectors, stayers	-2.0	98.6	0.5	98.2	0.0	98.6	-0.2	98.6
Non-dirty sectors, switchers	-1.9	0.2	5.9	0.5	0.1	0.1	-0.1	0.2
Dirty sectors, stayers	-13.8	0.9	-11.9	0.9	-11.9	0.9	-12.2	0.9
Dirty sectors, switchers	-7.6	0.4	-5.9	0.3	-5.6	0.4	-5.9	0.4
Aggregate	-2.5	100.0	-0.7	100.0	0.0	100.0	-0.2	100.0
Mexico	Wasteful Spending		Green Subsidy		Useful Spending		Education Subsidy	
	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)
Non-dirty sectors, stayers	-1.9	98.6	1.5	98.4	0.5	98.6	0.3	98.6
Non-dirty sectors, switchers	-1.9	0.2	13.7	0.4	0.7	0.2	0.3	0.2
Dirty sectors, stayers	-14.5	0.9	-13.1	0.9	-12.8	0.9	-12.6	0.9
Dirty sectors, switchers	-8.1	0.3	-6.6	0.3	-5.9	0.3	-6.1	0.3
Aggregate	-2.7	100.0	-0.8	100.0	0.4	100.0	0.0	100.0
United States	Wasteful Spending		Green Subsidy		Useful Spending		Education Subsidy	
	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)	CE (%)	LFP (%)
Non-dirty sectors, stayers	-1.1	99.4	1.1	99.3	0.2	99.4	0.1	99.4
Non-dirty sectors, switchers	-1.0	0.1	9.5	0.1	0.2	0.1	0.1	0.1
Dirty sectors, stayers	-12.9	0.4	-11.5	0.4	-11.9	0.4	-11.9	0.4
Dirty sectors, switchers	-6.8	0.1	-5.7	0.1	-5.7	0.1	-5.7	0.1
Aggregate	-1.1	100.0	-0.3	100.0	0.1	100.0	0.1	100.0

Note: CE = consumption equivalents, LFP = labor force participation.

Table 2 shows that workers who remain in the dirty sectors (oil, coal and gas) experience the largest decline in welfare. Take the United States as an example. In the wasteful spending scenario, the welfare of stayers in the dirty sectors declines by 12.9%. This loss is approximately double the one experienced by those who switch from the dirty sectors (6.8%) and almost 12 times the loss witnessed by non-dirty workers (stayers and switchers). Similar numbers are found for the other counterfactuals and countries (see Table 2). This decline in welfare is due to the reduction in labor demand and wages in the taxed sectors. The measure of workers directly affected by the introduction of the carbon tax, however, is relatively small—at most 1.9% of the labor force in our sample of countries (see Table C11). Due to general equilibrium effects, labor reallocation also takes place in the non-dirty sectors. Workers from the non-dirty sectors experience welfare gains in most counterfactuals (other than the wasteful spending scenario). This gain is especially large for those workers who switch sectors.

5.3 The Role of Worker Heterogeneity

In our benchmark model, workers have different abilities to work in each sector. For instance, some are more productive in dirty energy sectors while others have a comparative advantage in non-energy sectors. We now explore the role that this worker heterogeneity plays in our main results. In our model, workers' abilities are distributed according to a Frechét distribution with parameter λ. Since higher lambdas mean a less dispersed distribution of abilities, we increase λ to make workers more homogeneous.[13] With homogeneous workers, welfare losses are equalized across the four worker groups by construction. All groups witness a welfare decline of 1.4% in the United States under wasteful spending as opposed to a spectrum of losses between 1% and 12.9% when heterogeneity is featured (see Panel A in Table 3).

Panel B in Table 3 compares our benchmark aggregate results with this version with homogeneous workers. For every tax rebate scenario, output, consumption and welfare are lower with homogeneous workers. Therefore,

[13] We increase λ from 2.6 to 600 such that skills are essentially uniformly distributed.

Table 3: Role of Worker Heterogeneity in the United States

	Heterogeneous Workers			Homogeneous Workers		
Panel A - Distributional Effects						
Wasteful Spending	CE(%)	LFP(%)	Ratio*	CE(%)	LFP(%)	Ratio*
Non-dirty sectors, stayers	-1.1	99.4	1.0	-1.4	99.4	1.0
Non-dirty sectors, switchers	-1.0	0.1	0.9	-1.4	0.1	1.0
Dirty sectors, stayers	-12.9	0.4	12.2	-1.4	0.4	1.0
Dirty sectors, switchers	-6.8	0.1	6.5	-1.4	0.1	1.0
Panel B - Aggregate Effects						
	GDP	Consumption	Cons. Equiv.	GDP	Consumption	Cons. Equiv.
Wasteful Spending	-0.6	-1.7	-1.1	-0.9	-2.0	-1.4
Green Subsidy	-0.3	-0.3	-0.3	-0.4	-0.4	-0.5
Useful Spending	-0.5	-0.5	0.1	-0.8	-0.8	-0.2
Education Subsidy	0.4	-0.7	0.1	0.1	-1.0	-0.3
Household Transfers	-1.9	-1.8	1.1	-2.2	-2.1	1.0

*Ratio of welfare loss of each worker category relative to the non-dirty stayers.

modeling worker heterogeneity is key, both to understand the distributional effects and to correctly quantify the aggregate effects of climate change mitigation policies.

6 Concluding Remarks

This paper quantifies the aggregate and distributional effects of climate change mitigation policies within and across countries. Our results for the United States show that, to achieve its original Paris Agreement Goal, a carbon tax of 32.3% is needed and it causes a drop in GDP of at most 0.6%. Applying the same climate policy to other countries in our sample (Brazil, Canada, China, India and Mexico) yields drops in output ranging from 0.5% (Brazil) to 2.1% (China). The heterogeneity in the results is due to varying degrees of importance of the taxed energy sectors in the respective economies in terms of value added, intermediate consumption and labor force shares. These adverse effects on GDP can be partially or entirely offset through tax rebates.

Despite the small effects on output from imposing a carbon tax, there is significant heterogeneity at the sectoral level. The dirty energy sectors exposed to the carbon tax witness the largest drop in wages, and consequently the largest labor outflow. However, by examining the skill distribution, we find that less-talented workers in dirty energy production reallocate away from the taxed sectors into other sectors in the economy, while workers with a comparative advantage in dirty energy production remain and end up bearing most of the cost from the drop in wages. These workers, however, constitute a small fraction of total employment.

While our model featured considerable heterogeneity in terms of production structure and worker skills, it abstracted from tackling some margins. For instance, interesting insights can come from integrating our framework with a richer description from the demand side. Individuals with different income levels are likely to consume distinct baskets of goods. Another possibility is to study the entire time path of adjustment in response to climate policies. We leave these issues for future research.

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Online Appendix

A Appendix – Theory

A.1 Proposition 1 - Occupational Shares

The fraction of workers choosing to work in sector j is denoted by q_j. For simplicity, we present below the fraction of people who choose to work in sector 1 and this calculation procedure can be replicated to all sectors WLOG.

$$
\begin{aligned}
q_1 &= Pr(\tilde{w}_1 z_1 > \tilde{w}_j z_j \ \ \forall \ \ j \neq 1) \\
&= \mathbb{E}\left[Pr(\tilde{w}_1 z_1 > \tilde{w}_j z_j \ \ \forall \ \ j \neq 1 \ \mid \ z_1)\right] \\
&= \mathbb{E}\left[Pr(z_j < \frac{\tilde{w}_1 z_1}{\tilde{w}_j} \ \ \forall \ \ j \neq 1 \ \mid \ z_1)\right] \\
&= \int f(z_1) F(\beta_2 z_1) F(\beta_3 z_1)..F(\beta_j z_1)..F(\beta_J z_1) dz_1 \ \ where \ \ \beta_j = \frac{\tilde{w}_1}{\tilde{w}_j}
\end{aligned}
$$

This is as if we are taking the derivative with respect to the first argument of the new joint distribution $F(z_1, \beta_2 z_1, ..., \beta_J z_1)$, so q_1 is now:

$$
\begin{aligned}
q_1 &= \int_0^\infty F_1(z_1, \beta_2 z_1, \beta_3 z_1, .., \beta_j z_1, .., \beta_J z_1) dz_1 \\
&= \int_0^\infty F_1(z, \beta_2 z, \beta_3 z, .., \beta_j z, .., \beta_J z) dz
\end{aligned}
$$

We know that $F(z_1, z_2, ..z_J) = \exp\Big(-\sum_{j=1}^J z_j^{-\lambda}\Big)$, so:

$$
\begin{aligned}
F(z, \beta_2 z, ..., \beta_J z) &= \exp\Big(-\sum_{j=1}^J \beta_j^{-\lambda} z^{-\lambda}\Big) \\
F_1(z, \beta_2 z, ..., \beta_J z) &= (-)(-\lambda) z^{-\lambda-1} \exp\Big(-\sum_{j=1}^J \beta_j^{-\lambda} z^{-\lambda}\Big) \\
F_1(z, \beta_2 z, ..., \beta_J z) &= \lambda z^{-\lambda-1} \exp\Big(-\sum_{j=1}^J \beta_j^{-\lambda} z^{-\lambda}\Big)
\end{aligned}
$$

q_1 is now:

$$
\begin{aligned}
q_1 &= \int_0^\infty \lambda z^{-\lambda-1} \exp\Big(-\sum_{j=1}^{J} \beta_j^{-\lambda} z^{-\lambda}\Big) dz \\
&= \int_0^\infty \lambda z^{-\lambda-1} \exp\Big(-z^{-\lambda}\bar{\beta}\Big) dz, \text{ where } \bar{\beta} = \sum_{j=1}^{J} \beta_j^{-\lambda} \\
&= \int_0^\infty \lambda z^{-\lambda-1} \exp\Big(-\Big[(\bar{\beta})^{\frac{-1}{\lambda}} z\Big]^{-\lambda}\Big) dz
\end{aligned}
$$

We proceed with integration by change of variables, let $z' = (\bar{\beta})^{\frac{-1}{\lambda}} z$, then $dz' = \big(\bar{\beta}\big)^{\frac{-1}{\lambda}} dz$, so if we replace z with z':

$$
\begin{aligned}
q_1 &= \int_0^\infty \lambda \Big[\big(\bar{\beta}\big)^{\frac{1}{\lambda}} z'\Big]^{-\lambda-1} \exp\Big(-(z')^{-\lambda}\Big) \big(\bar{\beta}\big)^{\frac{1}{\lambda}} dz' \\
&= \big(\bar{\beta}\big)^{-1} \int_0^\infty \lambda (z')^{-\lambda-1} \exp\Big(-(z')^{-\lambda}\Big) dz' \\
&= \big(\bar{\beta}\big)^{-1} \int_0^\infty dF(z') \\
&= \big(\bar{\beta}\big)^{-1} \\
&= \frac{1}{\bar{\beta}} \\
&= \frac{1}{\sum_{j=1}^{J} \Big(\frac{\tilde{w_1}^{-\lambda}}{\tilde{w_j}^{-\lambda}}\Big)} \\
&= \frac{\tilde{w_1}^{\lambda}}{\sum_{j=1}^{J} \tilde{w_j}^{\lambda}}
\end{aligned}
$$

More generally:

$$
q_j = \frac{\tilde{w_j}^{\lambda}}{\sum_{k=1}^{J} \tilde{w_k}^{\lambda}} \text{ for } j \in \{1, ..., J\}
$$

q_j therefore represents the equilibrium share of workers in sector j.

A.2 Proposition 2: Effective Labor

Following Hsieh et al. (2019), the total efficiency units in each occupation (including both talent and human capital accumulation) is number of workers in every sector, given by q_j, multiplied by average individual productivity given by $\mathbb{E}[h_j z_j]$.

Recall that h_j is given by:

$$\begin{aligned}
h_j(s_j, e_j) &= {s_j}^{\phi_j} {e_j}^{\eta} \\
h_j &= {s_j}^{\phi_j} \left[\frac{1}{\eta w_j z_j {s_j}^{\phi_j}} \right]^{\frac{\eta}{\eta-1}} \\
h_j &= ({s_j}^{\phi_j})^{1-\frac{\eta}{\eta-1}} (\eta w_j z_j)^{\frac{\eta}{1-\eta}} \\
h_j &= ({s_j}^{\phi_j})^{\frac{1}{1-\eta}} \big(\eta w_j\big)^{\frac{\eta}{1-\eta}} {z_j}^{\frac{\eta}{1-\eta}}
\end{aligned}$$

$h_j z_j$ is now given by:

$$\begin{aligned}
h_j z_j &= ({s_j}^{\phi_j})^{\frac{1}{1-\eta}} \big(\eta w_j\big)^{\frac{\eta}{1-\eta}} {z_j}^{\frac{\eta}{1-\eta}} \cdot z_j \\
h_j z_j &= ({s_j}^{\phi_j})^{\frac{1}{1-\eta}} \big(\eta w_j\big)^{\frac{\eta}{1-\eta}} {z_j}^{\frac{1}{1-\eta}} \\
\mathbb{E}[h_j z_j] &= ({s_j}^{\phi_j})^{\frac{1}{1-\eta}} \big(\eta w_j\big)^{\frac{\eta}{1-\eta}} \mathbb{E}[{z_j}^{\frac{1}{1-\eta}} | \text{person works in sector j}]
\end{aligned}$$

Next step is to calculate $\mathbb{E}[z_j^{\frac{1}{1-\eta}} | \text{person works in sector j}]$. In order to do so, we first calculate $\mathbb{E}[z_j^x | \text{person works in sector j}]$, where x is some positive exponent.

As shown during the derivations of the occupational share, the new conditional distribution of individual ability z_j given that the worker sorts into sector j, is given by $G(z) = F(\beta_1 z, \beta_2 z, ..., \beta_J z) = \exp\Big(-\sum_{j=1}^{J} \beta_j^{-\lambda} z^{-\lambda} \Big) = \exp\Big(-\frac{1}{q_j} z^{-\lambda} \Big)$. So the conditional distribution, $G(z)$, is itself Fréchet distributed, with a scaling parameter of q_j. As such, we now have the following:

$$\begin{aligned}
\mathbb{E}[z_j^x] &= \int_0^{\infty} z^x dG(z) \\
&= \int_0^{\infty} \lambda \frac{1}{q_j} z^{-\lambda-1+x} e^{-\frac{1}{q_j} z^{-\lambda}} dz
\end{aligned}$$

Using change of variables, $y = \frac{1}{q_j} z^{-\lambda}$, we show that:

$$\begin{aligned}
\mathbb{E}[z_j^x] &= \frac{1}{q_j}^{\frac{x}{\lambda}} \int_0^\infty y^{-\frac{x}{\lambda}} e^{-y} dy \\
&= \frac{1}{q_j}^{\frac{x}{\lambda}} \Gamma(1 - \frac{x}{\lambda}) \\
&= q_j^{-\frac{x}{\lambda}} \Gamma(1 - \frac{x}{\lambda})
\end{aligned}$$

So for $x = \frac{1}{1-\eta}$, we have:

$$\begin{aligned}
\mathbb{E}[z_j^{\frac{1}{1-\eta}} | \text{person works in sector j}] &= \frac{1}{q_j}^{\frac{1}{\lambda}\frac{1}{1-\eta}} \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta}) \\
&= q_j^{-\frac{1}{\lambda}\frac{1}{1-\eta}} \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta})
\end{aligned}$$

So average productivity is now:

$$\text{Avg Productivity}_j = \mathbb{E}[h_j z_j] = ({s_j}^{\phi_j})^{\frac{1}{1-\eta}} \left(\eta w_j\right)^{\frac{\eta}{1-\eta}} q_j^{-\frac{1}{\lambda}\frac{1}{1-\eta}} \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta}) \tag{9}$$

Note that L_j^{supply} is sum of all individual productivities (i.e. total efficiency units of labor) employed in sector j, which is given by $L_j^{supply} = q_j \cdot \mathbb{E}[h_j z_j]$.

$$L_j^{supply} = (s^{\phi_j})^{\frac{1}{1-\eta}} \left(\eta w_j\right)^{\frac{\eta}{1-\eta}} q_j^{1-\frac{1}{\lambda}\frac{1}{1-\eta}} \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta}) \tag{10}$$

To investigate the partial derivative of L_j with respect to earnings $\tilde{w}_j$, we expand q_j in the equation of effective labor supply and get the following:

$$L_j^e = (s^{\phi_j})^{\frac{1}{1-\eta}} \left(\eta w_j\right)^{\frac{\eta}{1-\eta}} \left(\frac{\tilde{w_j}^{\lambda}}{\sum_{k=1}^{J} \tilde{w_k}^{\lambda}} \right)^{1-\frac{1}{\lambda}\frac{1}{1-\eta}} \Gamma(1 - \frac{1}{\lambda}\frac{1}{1-\eta})$$

B Details on Calibration

Table B1 lists all the model's parameters and classifies them according to the required calibration procedure.

Table B1: List of Parameters

	Externally Calibrated Parameters	**Data Source**
J	number of sectors	WIOD data
ν_{jk}	input-output shares	WIOD data
β_j^L	labor shares	WIOD data
$g_{\text{oil}} = 84.6\%$	carbon intensity of oil	Golosov et al. (2014)
$g_{\text{coal}} = 71.6\%$	carbon intensity of coal	Golosov et al. (2014)
$g_{\text{natural gas}} = 73.4\%$	carbon intensity of natural gas	IPCC (2006)
$g_{\text{green}} = 0\%$	carbon intensity of green	Golosov et al. (2014)
γ	consumption weight in the utility function	Mincerian estimate using IPUMS data
η	expenditure on education (% of GDP)	World Development Indicators
	Internally Calibrated Parameters	**Moment(s) Targeted**
σ_j	expenditure shares in final good	Sectoral value added from WIOD data
ϕ_j	returns of schooling in sector j	Average relative wages using WIOD data
λ	Fréchet dispersion parameter	Coefficient of variation in earnings from IPUMS data

The calibration relies on two major data sources: World Input Output Database (WIOD) and the Integrated Public Use Micro-data Series (IPUMS). Both databases present the sectors according to the International Standard Industrial Classification (ISIC) of all economic activities developed by the United Nations, however IPUMS conforms to a top level aggregation of 15 intermediate goods sectors, which we will refer to when aggregating the data of the 35 sectors in the WIOD input-output tables. In order to do so, we first collapse the 35 sectors in the WIOD tables to the top-level ISIC rev 4 classification as presented in the first column of Table B2. Second, we collapse the 21 sectors into the 15 sectors presented in IPUMS databases. Additionally, since the focus of this paper is on taxing dirty energy producing sectors in the economy, we create an aggregate energy sector by merging 'Mining and Quarrying' and 'Electricity' sectors; the sectoral breakdown is now represented in the second column of Table B2. Third, we split the aggregate energy sector into four energy producing sectors: oil, coal, natural gas and green according to the WIOD environmental accounts on gross energy use by sector and energy commodity. As such we end up with 18 intermediate goods sectors (J=18), which are presented in the third column of Table B2.

Table B2: Intermediate Goods Sectors

	Sectors (J=21) ISIC Rev4: Top-level Aggregation		Sectors (J=15) IPUMS Aggregation		Sectors (J=18) Authors' Aggregation
A	Agriculture, hunting, forestry and fishing	A	Agriculture, hunting, forestry and fishing	1.	Agriculture, hunting, forestry and fishing
B	Mining and Quarrying	C	Manufacturing	2.	Manufacturing
C	Manufacturing	E	Water supply	3.	Water supply
D	Electricity, gas, steam and air conditioning supply	F	Construction	4.	Construction
E	Water supply; sewerage, waste management and remediation activities	G	Wholesale and retail trade	5.	Wholesale and retail trade
F	Construction	H,J	Transport, storage and communications	6.	Transport, storage and communications
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	I	Accommodation and food service activities	7.	Accommodation and food service activities
H	Transportation and storage	K	Financial and insurance activities	8.	Financial and insurance activities
I	Accommodation and food service activities	L,M,N	Real estate, renting and business activities	9.	Real estate, renting and business activities
J	Information and communication	O	Public administration and defence	10.	Public administration and defence
K	Financial and insurance activities	P	Education	11.	Education
L	Real estate activities	Q	Health and social work	12.	Health and social work
M	Professional, scientific and technical activities	R,S,U	Arts and other service activities	13.	Arts and other service activities
N	Administrative and support service activities	T	Private household services	14.	Private household services
O	Public administration and defence; compulsory social security	B,D	Total Energy	15.	Oil Energy Production
P	Education			16.	Coal Energy Production
Q	Human health and social work activities			17.	Natural Gas Energy Production
R	Arts, entertainment and recreation			18.	Green Energy Production
S	Other service activities				
T	Activities of households as employers; undifferentiated goods - and services-producing activities of households for own use				
U	Activities of extraterritorial organizations and bodies				

Now that the input-output table is aggregated into J = 18, we calculate the input output matrix ν which represents intersectoral elasticise, such that each entry ν_{jk}:

$$\nu_{jk} = \frac{\text{Input of sector k into sector j}}{\text{Sales of sector j}}$$

As already discussed, β_j^L is calculated by adhering to the constant-returns-to-scale characteristic of our production function, such that $\beta_j^L + \sum_{k=1}^{J} \nu_{jk} = 1$. These parameters are not presented in the Appendix for space purposes.

Table B3 presents the values for η, which represents the fraction of output spent on education in every country. The public expenditure series is obtained from World Development Indicators. We also refer to OECD for private and public expenditure on education, but that is only available for four countries in our sample.

Table B3: Expenditure on Education in Every Country

	Public expenditure on education (%GDP)	Labor Force Participation	η	Public and private expenditure on education (%GDP)	η
Brazil	6.24	63.88	0.10	5.69	0.09
Canada	5.27	65.07	0.08	5.95	0.09
China	3.52	67.99	0.05	-	-
India	3.84	49.29	0.08	-	-
Mexico	4.91	60.68	0.08	5.90	0.10
United States	4.96	62.05	0.08	6.09	0.10

As for the internally calibrated estimates, Table B4 presents the final expenditure shares of each intermediate good alongside the value added shares of each of the intermediate good sectors in the model and in the data. Table B5 presents the estimated weight of consumption in utility γ, in every country. Table B6 demonstrates the sector-specific elasticity of human capital accumulation to schooling years in each country. Finally, Table B7 presents the Fréchet Parameter and variation coefficient of wages for each country in our sample.

Table B4: Intermediate Goods Sectors: Value-Added and Final Expenditure Shares

Sector	Brazil		Canada		China		India		Mexico		United States	
	VA_j (%)	σ_j	VA_j (%)	σ_j	VA_j (%)	σ_j	VA_j (%)	σ_j	VA_j (%)	σ_j	VA_j (%)	σ_j
1. Agriculture, hunting, forestry and fishing	5.2%	0.038	1.6%	0.018	9.4%	0.036	14.8%	0.111	3.3%	0.016	1.2%	0.005
2. Manufacturing	14.6%	0.222	11.6%	0.087	30.1%	0.329	16.6%	0.293	18.8%	0.228	12.4%	0.131
3. Water supply	0.7%	0.004	0.3%	0.000	0.3%	0.002	0.2%	0.002	0.4%	0.001	0.3%	0.000
4. Construction	6.7%	0.107	7.7%	0.141	6.8%	0.261	7.2%	0.137	7.6%	0.125	3.8%	0.055
5. Wholesale and retail trade	12.4%	0.094	10.5%	0.106	9.7%	0.048	17.1%	0.087	16.8%	0.141	12.2%	0.131
6. Transport, storage and communications	8.0%	0.057	8.0%	0.060	7.2%	0.036	11.6%	0.110	7.9%	0.105	9.1%	0.079
7. Hotels and restaurants	2.4%	0.031	2.1%	0.027	1.9%	0.021	1.4%	0.023	2.2%	0.027	2.8%	0.039
8. Financial services and insurance	6.3%	0.044	5.5%	0.042	6.0%	0.013	5.5%	0.020	3.5%	0.029	7.0%	0.055
9. Public administration and defense	16.6%	0.089	19.5%	0.142	9.7%	0.061	7.7%	0.071	17.8%	0.105	23.1%	0.149
10. Real estate, renting and business activities	9.6%	0.125	9.0%	0.150	4.0%	0.067	6.7%	0.063	4.4%	0.064	13.1%	0.179
11. Education	5.5%	0.066	5.4%	0.063	3.3%	0.050	4.0%	0.040	4.3%	0.049	1.1%	0.016
12. Health and social work	4.2%	0.060	6.3%	0.063	1.8%	0.049	1.5%	0.021	2.3%	0.034	7.1%	0.116
13. Other services activities	1.8%	0.027	2.1%	0.025	2.3%	0.021	2.4%	0.021	1.6%	0.020	2.6%	0.031
14. Private households services	1.1%	0.011	0.0%	0.000	0.0%	0.000	0.0%	0.000	0.5%	0.005	0.1%	0.001
15. Oil energy production	1.7%	0.013	4.9%	0.025	1.2%	0.006	0.6%	0.000	4.3%	0.024	1.3%	0.002
16. Coal energy production	0.1%	0.000	0.5%	0.006	2.8%	0.000	0.9%	0.000	0.3%	0.004	0.7%	0.007
17. Natural gas energy production	0.3%	0.000	2.1%	0.018	0.3%	0.000	0.1%	0.000	2.0%	0.014	0.9%	0.000
18. Green energy production	2.9%	0.011	2.9%	0.028	3.2%	0.000	1.6%	0.000	2.0%	0.011	1.2%	0.002

Table B5: Consumption Weight in Utility Function for all Countries in the Sample

Country	Consumption Weight (γ)
Brazil	0.3258
Canada	0.4060
China	0.6644
India	0.3809
Mexico	0.5006
United States	0.3176

Table B6: Relative Sectoral Wages and Sector-Specific Elasticity of Human Capital Accumulation to Schooling Years

Sector	Brazil		Canada		China		India		Mexico		US	
	$\frac{w_j}{w_{Agri}}$	ϕ_j	$\frac{w_j}{w_{Agri}}$	ϕ_j	$\frac{w_j}{w_{Agri}}$	ϕ_j	$\frac{w_j}{w_{Agri}}$	ϕ_j	$\frac{w_j}{w_{Agri}}$	ϕ_j	$\frac{w_j}{w_{Agri}}$	ϕ_j
1. Agriculture, hunting, forestry and fishing	1.0	0.59	1.0	1.82	1.0	0.6	1.0	0.61	1.0	0.55	1.0	2.81
2. Manufacturing	2.1	0.86	1.0	0.84	1.7	0.8	1.3	0.78	2.5	0.71	1.4	1.89
3. Water supply	1.9	2.49	1.0	2.98	10.1	58.4	4.2	8.19	2.7	5.32	1.3	4.98
4. Construction	1.0	0.52	1.2	1.24	1.4	1.2	1.2	1.00	2.6	1.29	1.5	2.79
5. Wholesale and retail trade	1.2	0.48	0.7	0.52	0.9	0.5	5.7	3.07	3.5	1.24	0.9	1.33
6. Transport, storage and communications	2.7	1.39	1.0	1.04	2.5	2.7	2.3	1.63	4.2	2.27	1.5	2.13
7. Hotels and restaurants	0.9	0.75	0.4	0.56	1.7	3.1	2.0	2.69	2.7	2.55	0.5	1.17
8. Financial services and insurance	6.2	3.07	1.1	1.33	3.3	4.1	4.4	3.40	9.3	7.76	2.2	3.04
9. Public administration and defense	1.5	0.53	0.9	0.63	3.1	3.0	2.5	1.97	4.1	1.46	1.3	1.44
10. Real estate, renting and business activities	4.5	2.05	1.2	1.22	1.7	2.2	5.1	3.67	4.7	3.37	1.3	1.76
11. Education	2.6	1.57	1.3	1.57	1.4	1.8	1.6	1.67	4.4	3.16	0.9	2.77
12. Health and social work	2.4	1.60	1.1	1.20	1.3	2.3	2.2	2.89	6.2	6.18	1.1	1.78
13. Other services activities	0.6	0.50	0.6	0.96	0.6	0.6	2.6	2.89	2.1	2.24	1.2	2.55
14. Private households services	0.5	0.62	0.0	0.09	0.0	1.8	0.0	3.10	6.2	12.24	0.8	5.09
15. Energy average (weighted by LFP)	6.6	4.57	1.9	2.54	3.1	5.3	3.3	3.66	6.5	5.78	2.4	5.23

Table B7: Fréchet Parameter and Variation Coefficient of Wages by Country

Country	Data Sample Size	Data Estimate of Variation Coefficient	Model Estimate of Variation Coefficient	Fréchet Parameter λ
Brazil	8,241,143	6.37	6.37	2.32
Canada	463,677	1.08	1.08	2.72
China	24,915	0.91	0.91	2.72
India	85,855	0.90	0.90	2.80
Mexico	3,056,419	4.32	4.32	2.33
United States	1,488,316	1.41	1.41	2.60

Table B8: Untargeted Labor Force Participation Moment by Country

Sector	Brazil		Canada		China		India		Mexico		United States	
	LFP Data	LFP Model Untargeted	LFP Data	LFP Model Untargeted	LFP Data	LFP Model Untargeted	LFP Data	LFP Model Untargeted	LFP Data	LFP Model Untargeted	LFP Data	Model Untargeted
1. Agriculture, hunting, forestry and fishing	10.2	7.0	1.2	0.9	23.8	14.1	33.2	27.9	12.4	6.5	1.0	0.7
2. Manufacturing	11.9	15.7	11.5	13.1	19.6	40.5	14.4	27.5	16.0	32.5	8.7	11.7
3. Water supply	0.5	0.2	0.2	0.1	0.0	0.0	0.1	0.0	0.4	0.1	0.3	0.1
4. Construction	9.6	9.7	7.4	6.4	8.4	6.8	16.7	9.9	16.4	8.7	4.3	2.1
5. Wholesale and retail trade	16.8	18.5	17.6	15.5	11.2	15.8	5.7	6.9	14.0	19.9	15.1	17.0
6. Transport, storage and communications	5.3	5.7	7.3	7.8	3.9	3.7	7.6	10.4	7.6	5.3	7.1	7.4
7. Hotels and restaurants	4.6	2.8	7.0	3.0	2.6	0.9	1.4	0.7	3.5	1.3	8.7	4.4
8. Financial services and insurance	1.3	1.6	4.5	4.4	2.0	2.1	1.5	1.9	1.5	0.4	4.0	3.4
9. Public administration and defense	9.3	23.8	10.8	26.1	3.2	4.5	4.2	5.5	2.1	18.4	14.6	29.7
10. Real estate, renting and business activities	5.9	4.3	8.4	7.6	5.4	2.5	4.6	2.0	9.2	1.8	16.7	13.4
11. Education	7.0	3.4	7.7	3.6	5.3	2.4	6.1	3.4	9.0	1.9	2.3	0.6
12. Health and social work	4.4	2.5	9.2	5.4	3.0	1.1	1.6	0.6	3.5	0.4	12.5	7.2
13. Other services activities	5.6	2.7	4.9	2.2	8.9	3.5	1.4	1.1	2.2	1.1	3.8	1.6
14. Private households services	7.1	1.5	-		0.0	0.0	0.0	0.0	0.8	0.0	0.2	0.0
15. Oil energy production	0.2	0.2	1.1	1.9	0.4	0.3	0.3	0.6	0.7	0.8	0.3	0.2
16. Coal energy production	0.0	0.0	0.1	0.2	1.4	0.9	0.5	0.6	0.1	0.1	0.2	0.1
17. Natural gas energy production	0.0	0.0	0.4	0.8	0.1	0.1	0.1	0.1	0.4	0.4	0.2	0.2
18. Green energy production	0.3	0.4	0.6	1.1	0.7	0.8	0.5	0.8	0.3	0.4	0.3	0.2
Model Fit (Correlation between actual and model LFP series)	80.9%		78.6%		80.2%		89.1%		65.6%		85.3%	

Table B9: Data Sources by Country

Country	Data	Year	Source
Brazil	Input Output Table	2014	WIOD
	Environmental Accounts to get energy input mix by sector	2009	WIOD
	CO_2 Emissions	2009	WIOD
	Sectoral Labor Force Participation	2014	WIOD
	Sectoral Labor Compensation	2014	WIOD
	Data on Income Earned	2010	IPUMS
	Education Attainment by Sector	2010	IPUMS
	Public Expenditure on Education (% of GDP)	2015	WDI
	Total Labor Force Participation Rate (%)	2019	WDI
Canada	Input Output Table	2014	WIOD
	Environmental Accounts to get energy input mix by sector	2009	WIOD
	CO_2 Emissions	2009	WIOD
	Sectoral Labor Force Participation	2014	WIOD
	Sectoral Labor Compensation	2014	WIOD
	Data on Income Earned	2011	IPUMS
	Education Attainment by Sector	2011	IPUMS
	Public Expenditure on Education (% of GDP)	2011	WDI
	Total Labor Force Participation Rate (%)	2019	WDI
China	Input Output Table	2014	WIOD
	Environmental Accounts to get energy input mix by sector	2009	WIOD
	CO_2 Emissions	2009	WIOD
	Sectoral Labor Force Participation	2014	WIOD
	Sectoral Labor Compensation	2014	WIOD
	Data on Income Earned	2013	CHIP
	Education Attainment by Sector	2013	CHIP
	Public Expenditure on Education (% of GDP)	2019	MoF China
	Total Labor Force Participation Rate (%)	2019	WDI
India	Input Output Table	2014	WIOD
	Environmental Accounts to get energy input mix by sector	2009	WIOD
	CO_2 Emissions	2009	WIOD
	Sectoral Labor Force Participation	2014	WIOD
	Sectoral Labor Compensation	2014	WIOD
	Data on Wage Earned	2004	IPUMS
	Education Attainment by Sector	2004	IPUMS
	Public Expenditure on Education (% of GDP)	2013	WDI
	Total Labor Force Participation Rate (%)	2019	WDI
Mexico	Input Output Table	2014	WIOD
	Environmental Accounts to get energy input mix by sector	2009	WIOD
	CO_2 Emissions	2009	WIOD
	Sectoral Labor Force Participation	2014	WIOD
	Sectoral Labor Compensation	2014	WIOD
	Data on Income Earned	2015	IPUMS
	Education Attainment by Sector	2015	IPUMS
	Public Expenditure on Education (% of GDP)	2016	WDI
	Total Labor Force Participation Rate (%)	2019	WDI
United States	Input Output Table	2014	WIOD
	Environmental Accounts to get energy input mix by sector	2009	WIOD
	CO_2 Emissions	2009	WIOD
	Sectoral Labor Force Participation	2014	WIOD
	Sectoral Labor Compensation	2014	WIOD
	Data on Income Earned	2015	IPUMS
	Education Attainment by Sector	2015	IPUMS
	Public Expenditure on Education (% of GDP)	2014	WDI
	Total Labor Force Participation Rate (%)	2019	WDI

C More Detailed Results

Table C10: Percentage Change in CO_2 Emissions by Source, Country and Recycling Scheme

Wasteful Spending Scenario

	%Δ Oil Emissions	%Δ Coal Emissions	%Δ Natural Gas Emissions	%Δ Green Emissions	%Δ Non-energy Emissions	**%Δ Total Fossil Fuel Emissions**	**%Δ Total Emissions**	Unconditional Target Stated in Nationally Determined Contribution
Brazil	-27.7%	-26.6%	-26.7%	NaN	-0.4%	-27.5%	-25.9%	37% below 2005 by 2025, 43% by 2030 (indicative)
Canada	-27.9%	-25.4%	-25.1%	NaN	-1.2%	-26.6%	-24.0%	30% below 2005 levels by 2030 (unchanged from NDC)
China	-29.5%	-35.0%	-28.8%	NaN	-2.6%	-34.0%	-32.1%	60-65% carbon intensity reduction by 2030
India	-28.3%	-30.7%	-27.6%	NaN	-1.0%	-29.9%	-28.2%	33 to 35% carbon intensity reduction over 2005 levels by 2030
Mexico	-27.8%	-24.4%	-25.0%	NaN	-1.0%	-26.8%	-25.3%	25% below BAU by 2030 (22% of GHG and a reduction of 51% of Black Carbon).
United States	-27.7%	-26.6%	-25.3%	NaN	-0.7%	-26.8%	-26.0%	26-28% below 2005 levels by 2025

Green Subsidy Scenario

	%Δ Oil Emissions	%Δ Coal Emissions	%Δ Natural Gas Emissions	%Δ Green Emissions	%Δ Non-energy Emissions	**%Δ Total Fossil Fuel Emissions**	**%Δ Total Emissions**	Unconditional Target Stated in Nationally Determined Contribution
Brazil	-27.3%	-22.8%	-23.5%	NaN	0.0%	-26.5%	-25.0%	37% below 2005 by 2025, 43% by 2030 (indicative)
Canada	-27.3%	-23.2%	-23.7%	NaN	0.0%	-25.5%	-22.9%	30% below 2005 levels by 2030 (unchanged from NDC)
China	-28.1%	-27.5%	-25.6%	NaN	-1.0%	-27.5%	-25.9%	60-65% carbon intensity reduction by 2030
India	-27.8%	-26.7%	-25.5%	NaN	-0.5%	-26.9%	-25.4%	33 to 35% carbon intensity reduction over 2005 levels by 2030
Mexico	-27.4%	-23.2%	-23.8%	NaN	-0.1%	-26.1%	-24.6%	25% below BAU by 2030 (22% of GHG and a reduction of 51% of Black Carbon).
United States	-27.3%	-23.1%	-23.7%	NaN	0.0%	-25.0%	-24.3%	26-28% below 2005 levels by 2025

Useful Spending Scenario

	%Δ Oil Emissions	%Δ Coal Emissions	%Δ Natural Gas Emissions	%Δ Green Emissions	%Δ Non-energy Emissions	**%Δ Total Fossil Fuel Emissions**	**%Δ Total Emissions**	Unconditional Target Stated in Nationally Determined Contribution
Brazil	-27.3%	-25.8%	-26.0%	NaN	0.2%	-27.1%	-25.5%	37% below 2005 by 2025, 43% by 2030 (indicative)
Canada	-26.3%	-24.9%	-24.2%	NaN	0.8%	-25.4%	-22.8%	30% below 2005 levels by 2030 (unchanged from NDC)
China	-27.2%	-31.9%	-25.5%	NaN	0.5%	-31.0%	-29.1%	60-65% carbon intensity reduction by 2030
India	-26.8%	-29.1%	-25.9%	NaN	0.1%	-28.3%	-26.7%	33 to 35% carbon intensity reduction over 2005 levels by 2030
Mexico	-26.6%	-24.2%	-23.9%	NaN	0.7%	-25.7%	-24.2%	25% below BAU by 2030 (22% of GHG and a reduction of 51% of Black Carbon).
United States	-26.9%	-26.3%	-24.3%	NaN	0.1%	-26.1%	-25.3%	26-28% below 2005 levels by 2025

Education Subsidy Scenario

	%Δ Oil Emissions	%Δ Coal Emissions	%Δ Natural Gas Emissions	%Δ Green Emissions	%Δ Non-energy Emissions	**%Δ Total Fossil Fuel Emissions**	**%Δ Total Emissions**	Unconditional Target Stated in Nationally Determined Contribution
Brazil	-27.7%	-26.6%	-26.7%	NaN	-0.4%	-27.5%	-25.9%	37% below 2005 by 2025, 43% by 2030 (indicative)
Canada	-27.9%	-25.4%	-25.1%	NaN	-1.2%	-26.6%	-24.0%	30% below 2005 levels by 2030 (unchanged from NDC)
China	-29.5%	-35.0%	-28.8%	NaN	-2.6%	-34.0%	-32.1%	60-65% carbon intensity reduction by 2030
India	-28.3%	-30.7%	-27.6%	NaN	-1.0%	-29.9%	-28.2%	33 to 35% carbon intensity reduction over 2005 levels by 2030
Mexico	-27.8%	-24.4%	-25.0%	NaN	-1.0%	-26.8%	-25.3%	25% below BAU by 2030 (22% of GHG and a reduction of 51% of Black Carbon).
United States	-27.7%	-26.6%	-25.3%	NaN	-0.7%	-26.8%	-26.0%	26-28% below 2005 levels by 2025

Table C11: Sectoral Breakdown of Output, VA, Intermediate Consumption and Labor Force Participation by Country

	Brazil				**Canada**				China				**India**				**Mexico**				**United States**			
	Sales	VA	Int. Cons.	LFP	Sales	VA	Int. Cons.	LFP	Sales	VA	Int. Cons.	LFP	Sales	VA	Int. Cons.	LFP	Sales	VA	Int. Cons.	LFP	Sales	VA	Int. Cons.	LFP
1. Agriculture, hunting, forestry and fishing	4.5%	5.2%	3.7%	10.2%	2.3%	1.6%	3.1%	1.2%	5.3%	9.4%	3.2%	23.8%	10.4%	14.8%	5.5%	33.2%	3.0%	3.3%	2.7%	12.4%	1.6%	1.2%	2.0%	1.0%
2. Manufacturing	27.6%	14.6%	43.6%	11.9%	18.9%	11.6%	26.9%	11.5%	50.0%	30.1%	59.7%	19.6%	36.4%	16.6%	58.5%	14.4%	34.4%	18.8%	55.6%	16.0%	20.1%	12.4%	29.9%	8.7%
3. Water supply	0.6%	0.7%	0.4%	0.5%	0.2%	0.3%	0.1%	0.2%	0.2%	0.3%	0.2%	0.0%	0.2%	0.2%	0.2%	0.1%	0.4%	0.4%	0.3%	0.4%	0.3%	0.3%	0.4%	0.3%
4. Construction	7.2%	6.7%	7.8%	9.6%	8.9%	7.7%	10.3%	7.4%	9.6%	6.8%	10.9%	8.4%	9.9%	7.2%	12.8%	16.7%	7.8%	7.6%	8.1%	16.4%	3.9%	3.8%	4.0%	4.3%
5. Wholesale and retail trade	10.3%	12.4%	7.6%	16.8%	10.3%	10.5%	10.1%	17.6%	5.3%	9.7%	3.1%	11.2%	10.6%	17.1%	3.3%	5.7%	12.5%	16.8%	6.7%	14.0%	10.5%	12.2%	8.4%	15.1%
6. Transport, storage and communications	8.4%	8.0%	8.8%	5.3%	9.1%	8.0%	10.3%	7.3%	4.8%	7.2%	3.6%	3.9%	10.4%	11.6%	9.0%	7.6%	8.3%	7.9%	8.9%	7.6%	9.5%	9.1%	9.9%	7.1%
7. Hotels and restaurants	2.3%	2.4%	2.3%	4.6%	2.2%	2.1%	2.3%	7.0%	1.7%	1.9%	1.6%	2.6%	2.2%	1.4%	3.1%	1.4%	1.9%	2.2%	1.4%	3.5%	2.9%	2.8%	3.0%	8.7%
8. Financial services and insurance	5.5%	6.3%	4.5%	1.3%	5.6%	5.5%	5.8%	4.5%	2.9%	6.0%	1.3%	2.0%	3.4%	5.5%	1.1%	1.5%	3.1%	3.5%	2.6%	1.5%	7.0%	7.0%	7.1%	4.0%
9. Public administration and defense	11.7%	16.6%	5.7%	9.3%	15.9%	19.5%	12.0%	10.8%	5.6%	9.7%	3.7%	3.2%	4.8%	7.7%	1.6%	4.2%	11.8%	17.8%	3.7%	2.1%	19.4%	23.1%	14.7%	14.6%
10. Real estate, renting and business activities	7.2%	9.6%	4.2%	5.9%	8.6%	9.0%	8.1%	8.4%	2.4%	4.0%	1.6%	5.4%	3.5%	6.7%	0.0%	4.6%	3.7%	4.4%	2.7%	9.2%	11.1%	13.1%	8.5%	16.7%
11. Education	3.9%	5.5%	1.8%	7.0%	3.5%	5.4%	1.4%	7.7%	1.9%	3.3%	1.2%	5.3%	2.3%	4.0%	0.5%	6.1%	2.8%	4.3%	0.8%	9.0%	1.0%	1.1%	0.9%	2.3%
12. Health and social work	3.5%	4.2%	2.6%	4.4%	4.6%	6.3%	2.9%	9.2%	1.7%	1.8%	1.7%	3.0%	1.2%	1.5%	0.9%	1.6%	2.0%	2.3%	1.5%	3.5%	6.7%	7.1%	6.3%	12.5%
13. Other services activities	1.8%	1.8%	1.9%	5.6%	2.0%	2.1%	1.9%	4.9%	1.6%	2.3%	1.3%	8.9%	1.6%	2.4%	0.6%	1.4%	1.3%	1.6%	0.9%	2.2%	2.4%	2.6%	2.3%	3.8%
14. Private households services	0.6%	1.1%	0.0%	7.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.3%	0.5%	0.0%	0.8%	0.1%	0.1%	0.1%	0.2%
15. Oil energy production	1.5%	1.7%	1.3%	0.2%	3.7%	4.9%	2.3%	1.1%	1.0%	1.2%	0.8%	0.4%	0.6%	0.6%	0.5%	0.3%	3.2%	4.3%	1.8%	0.7%	1.0%	1.3%	0.6%	0.3%
16. Coal energy production	0.1%	0.1%	0.1%	0.0%	0.4%	0.5%	0.3%	0.1%	3.8%	2.8%	4.3%	1.4%	1.2%	0.9%	1.5%	0.5%	0.3%	0.3%	0.2%	0.1%	0.7%	0.7%	0.6%	0.2%
17. Natural gas energy production	0.4%	0.3%	0.4%	0.0%	1.5%	2.1%	0.9%	0.4%	0.3%	0.3%	0.3%	0.1%	0.2%	0.1%	0.2%	0.1%	1.7%	2.0%	1.3%	0.4%	0.8%	0.9%	0.5%	0.2%
18. Green energy production	2.9%	2.9%	3.0%	0.3%	2.1%	2.9%	1.3%	0.6%	2.0%	3.2%	1.4%	0.7%	1.2%	1.6%	0.7%	0.5%	1.5%	2.0%	0.9%	0.3%	1.0%	1.2%	0.7%	0.3%
Sum of total dirty energy production shares	2.0%	2.0%	1.9%	0.2%	5.6%	7.5%	3.5%	1.7%	5.1%	4.4%	5.4%	1.9%	1.9%	1.7%	2.1%	0.9%	5.2%	6.6%	3.3%	1.1%	2.4%	3.0%	1.8%	0.6%

D Introducing Wage-Wedges

In this subsection, we add wage-wedges to the case of Mexico, which had the lowest correlation between the untargeted labor force participation shares in the model and in the data. The model fit with the newly introduced wedges is now presented in table Table D12.

Results in Table D13 prove robust to the introduction of wedges showing that leaving the labor force participation shares untargeted in the model has little to no effect on the aforementioned aggregate effects.

Table D12: Model Fit Upon Introducing Wage-Wedges in Mexico

	Relative Wages		LFP	
	Data	**Model**	**Data**	**Model**
1. Agriculture, hunting, forestry and fishing	1.00	1.00	12.4%	14.4%
2. Manufacturing	2.49	2.49	16.0%	17.2%
3. Water supply	2.66	2.66	0.4%	0.3%
4. Construction	2.61	2.61	16.4%	18.2%
5. Wholesale and retail trade	3.54	3.54	14.0%	15.4%
6. Transport, storage and communications	4.24	4.24	7.6%	7.1%
7. Hotels and restaurants	2.73	2.73	3.5%	3.2%
8. Financial services and insurance	9.26	9.26	1.5%	1.0%
9. Public administration and defense	4.14	5.23	2.1%	2.2%
10. Real estate, renting and business activities	4.68	4.68	9.2%	6.9%
11. Education	4.38	4.38	9.0%	7.2%
12. Health and social work	6.23	6.23	3.5%	1.4%
13. Other services activities	2.11	2.11	2.2%	2.5%
14. Private households services	6.20	6.20	0.8%	0.1%
15. Oil energy production	6.46	6.50	0.7%	1.4%
16. Coal energy production			0.1%	0.1%
17. Natural gas energy production			0.4%	0.8%
18. Green energy production			0.3%	0.7%
Correlation	99.2%		98.3%	

Table D13: Comparing Main Results for Mexico With and Without Wage Wedges

Mexico - with wedges	**GDP**	**Consumption**	**Cons. Equiv.**
Wasteful Spending	-1.1	-3.3	-2.4
Green Subsidy	-0.7	-0.7	-0.8
Useful Spending	-0.9	-0.9	0.5
Education Subsidy	1.0	-1.3	-0.3
Mexico - without wedges	**GDP**	**Consumption**	**Cons. Equiv.**
Wasteful Spending	-1.1	-3.4	-2.2
Green Subsidy	-0.7	-0.7	-0.8
Useful Spending	-1.0	-1.0	0.4
Education Subsidy	1.0	-1.4	0.0