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Modeling the Income Dependence of Household Energy Consumption and its Implications for Climate Policy in China

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Modeling the Income Dependence of Household Energy Consumption and its Implications for Climate Policy in China

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Abstract: We estimate Engel Curves based on Chinese household microdata and show in general equilibrium simulations that they imply substantially lower energy demand and CO_2 emissions, relative to projections based on standard assumptions of unitary income elasticity. Income-driven shifts in consumption reduce the average welfare cost of emissions pricing by more than half. Climate policy is also less regressive, as rising income leads to rapid convergence in the energy intensity of consumption baskets and more evenly distributed welfare loss across households. Our findings underscore the importance of correctly accounting for the relationship between income and energy demand in high-growth economies.

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1. Introduction

Energy is central to the environmental and public health impacts of economic development. Household energy consumption in emerging economies plays a central role in projections of future energy use and the environmental externalities it causes, such as degraded air quality and global climate change (Wolfram *et al.*, 2012).

The demand for energy linked to household consumption exhibits substantial cross sectional variation across income levels, even within countries. This suggests that future growth in income may further shift consumption patterns and energy demand. As the bulk of growth in energy consumption and associated emissions is expected to come from fast-growing developing countries, understanding the implications of these shifts is crucial. Despite this, empirical estimates of how energy use changes as incomes rise (income elasticities) are often limited by a lack of data. As a result, analysts usually rely on assumptions—such as unitary income elasticities derived from homothetic preferences. We investigate the importance of these simplifications for projections and policy evaluation.

China is the world's largest developing economy, energy user, and emitter of CO_2. Outcomes in China will have implications for global energy use and hold lessons for other developing countries. Our analysis exploits the large existing variation in household incomes in China to identify the relationship between household income and expenditure patterns. We estimate Engel curves for energy goods using a new energy-specific survey of Chinese household consumption and for the indirect energy embodied in the production of all other goods using official consumption statistics and input-output tables. We employ flexible functional forms that allow for non-homothetic behavior and non-constant income elasticity, approximating a full rank demand system, and control for important co-variates. We perform estimations for urban and rural households in each province, capturing two policy-relevant dimensions of incidence in China (Ming & Zhao, 2006; Zhang *et al.*, 2013).

We then study the implications of our empirically-derived estimates on projections and policy costs in general equilibrium. To do so, we develop a novel methodology to calibrate a recursive-dynamic general equilibrium (GE) model to estimated Engel Curves as a function of between-period changes in income. The model provides projected outcomes for China based on the empirically-derived calibrated preferences. To evaluate the impact of income-driven shifts in consumption, we compare our simulation results with those based on a standard homothetic constant-elasticity-of-substitution (CES) demand system with unitary income elasticity. The GE model captures feedbacks between changing consumption patterns and supply, including production and trade flows, as well as interactions with energy and climate policy. These feedbacks would not be captured in a partial equilibrium study of shifting consumption patterns.

We also use the model to simulate a climate policy consisting of national CO_2 emissions targets implemented via a nationwide CO_2 price in all sectors. While stylized in nature, the policy is designed to be consistent with China's climate pledge of reducing energy intensity by 60-65% in 2030, relative to 2005. The model allows us to examine a number of the "channels of climate policy incidence" documented by Fullerton (2011).[1]

Finally, we decompose the general equilibrium effects of income-driven shifts in consumption patterns on the policy's welfare costs across household types. We disentangle the policy's impact on household incomes (which we refer to as "income side" impacts) from its impact on purchasing power ("consumption side" impacts). The later are determined by the interaction between relative price changes and household consumption patterns. We show that both are affected by the preference specification.

We believe our analysis to be the first to investigate the interactions between the income-driven dynamics of consumption patterns, energy demand and climate policy. We focus on three main findings. First, compared to unit-income elasticity homothetic preferences, our estimated Engel curves yield considerably lower projections of household and total demand for energy in China as well as lower associated CO_2 emissions. Household emissions in 2030 are 61% lower, and national emissions are reduced by 8%. This result reflects the fact that, in China, the energy and CO_2 intensity of consumption decreases with income at almost all income levels.

Second, moving to calibrated preferences lowers the average welfare cost of reaching a given emissions target. Climate policy is considerably less stringent, particularly for households as their consumption baskets grow relatively cleaner over time. Average welfare loss (measured as consumption loss) is 54% lower—good news for policy makers who seek to limit the impact of climate policy on domestic households. GDP loss is 11% lower, a smaller difference which reflects the fact that a portion of the residual burden of emissions reduction is shifted to other parts of the economy.

1 Our analysis captures five of the six "channels of incidence" from Fullerton (2011): (1) increased prices of carbon-intensive goods, (2) changes in relative returns to factors of production, (3) allocation of revenues from carbon pricing, (4) dynamic effects, (5) capitalization of all those effects into prices of land and other resources. We do not capture (6) benefits from improved environmental quality. A partial equilibrium analysis would only capture a subset of these channels.

Third, CO_2 pricing—which is initially very regressive—becomes more distributionally neutral under calibrated preferences. While variation in welfare impacts across income levels falls for both consumption and income side impacts, it decreases more than proportionally on the consumption side. Low income households, which are initially more exposed to carbon pricing through the consumption channel, reduce the CO_2 intensity of their consumption baskets faster than high income households. Shifting consumption patterns thus drive convergence in the CO_2 intensity of consumption across household types, which in turn reduces the variation in impacts across income levels. General equilibrium effects cause variation in income side impacts to decrease as well.

Calibrated preferences also reveal that income growth shifts household consumption away from goods which tend to be consumed near their location of production (such as agriculture and coal) and towards more easily traded goods (manufacturing and oil). As a result, the spatial colocation of the consumption and production of CO_2 will decrease over time, leading to a de-linking between the consumption and income side impacts across provinces. This and other general equilibrium effects alter the geographical ranking of winners and losers under climate policy.

Our results have implications for climate policy design. We show how empirically calibrated non-homothetic preferences can substantially alter baseline projections of CO_2 emissions growth, as well as the magnitude and distribution of policy costs. The 2015 Paris Climate Agreement commits all countries to act to mitigate CO_2 emissions (UFCCC, 2015; NDRC, 2015). As policy communities develop national mitigation plans and policies, distributional impacts are of major concern (Metcalf *et al.*, 2008; Rausch *et al.*, 2011; Zhang *et al.*, 2013). Our method can increase the empirical realism of projections that *ex ante* comparisons of climate policy effort are based on (Aldy *et al.*, 2015).

Our results imply that policy evaluation exercises assuming unitary income elasticities would tend to overstate the costs of climate policy in China. Studies to date, including some by the authors, typically make such assumptions (see for example Zhang (2000); Zhang *et al.* (2016a); Cao *et al.* (2009); Wang *et al.* (2009); Shi *et al.* (2010)). While our empirical estimates and their implications for projections and policy are likely specific to China, they suggest that income-driven changes in consumption patterns can affect energy and CO_2 emissions projections as well as the magnitude, distribution, and dynamics of policy incidence. These effects may be large in other parts of the developing world in which preexisting disparities in income are large and income levels are changing dramatically and unevenly over relatively short time horizons. Our results underscore the importance of correctly anticipating the effect of rising incomes on energy demand and understanding their implications in general equilibrium. We describe a methodology that can be applied to any country in which energy-specific household microdata is available.

2. Estimating the Relationship between Consumption Patterns and Income

2.1 Empirical Evidence for Non-homothetic Preferences

Since the foundational work of Engel (1895), Working (1943) and Leser (1963), scholars have recognized income as an important determinant of household consumption patterns. A large body of literature has focused on estimating income elasticities of household demand for goods and services, including housing (Carliner, 1973), electricity (Branch, 1993), food and agricultural products (Haque, 2005; Chern *et al.*, 2003), and studies that estimate elasticities for a wide range of consumption goods across multiple countries (Houthakker, 1957; Caron *et al.*, 2014). Many estimates of income elasticities of demand for goods and services are found to deviate from unity and to vary by income level. For example, the income elasticities of food (Engel's Law, Houthakker (1957)) and clothing (Schwabe's Law, Haque (2005)) are generally found to be lower than one. In the case of China, Zhou *et al.* (2012) find evidence that, in the process of economic development, some luxury goods such as beef, fish and poultry turn into necessities, implying elasticities that move from above to below unity as income rises.

Insights from the studies cited above, which rely on aggregate (often national) data to provide 'macro' estimates of the income-consumption relationship, have gradually been augmented by a body of analysis based on 'micro' household survey data. Such data allow more precise estimation of the relationship, better identification of the role of income, and capture the dynamics of adoption by differentiating between the intensive and the extensive margins of consumption. The latter is particularly important in the context of energy use where different types of energy may be consumed. Most 'micro' studies focusing on energy demand rely on developed-world surveys, such as from the European Union (Reinders *et al.*, 2003), the United States (Branch, 1993) or Denmark (Munksgaard *et al.*, 2000) although a small but growing literature focusses on the developing world where the dynamics are likely very different (see f.ex. Filippini & Pachauri (2004) for the use of household data in India). Much of this literature has focused on the relationship between household income and the adoption of specific energy-using consumer durables: Auffhammer & Wolfram (2014) document S-shaped adoption curves for a number of appliances using province-level data in China while Gertler *et al.* (2016) identifies such a relationship using micro-data from a Mexican conditional cash transfer program. Davis & Gertler (2015) document a very strong link between income and adoption of air conditioners and predict a very rapid increase in related energy use in middle-income countries. These sector-specific studies provide support for the conclusion that the income elasticity of energy demand not only differs from unity but also varies by income level.

Taking a 'macro' economy-wide approach, Caron & Fally (2016) provide cross-country evidence that the income elasticity of most sectors of the economy varies significantly from unity and is correlated with energy intensity in a way that affects energy intensities at the country level. However, in general the literature offers very little systematic 'micro'-based evidence of the effect of shifts in consumption on total energy demand.

Only a small number of studies investigating consumption patterns in China use micro data, due in part to the limited availability of household surveys in the country. One exception is China's Urban Household Income and Expenditure Survey collected by the National Bureau of Statistics (NBS) which is exploited by Liang *et al.* (2014) to estimate the relationship between income and energy demand in an Almost-Ideal Demand System (AIDS) model. They provide strong evidence that income elasticity varies across income groups, but do not estimate flexible Engel curves which span the full income spectrum. While the survey contains a large number of observations, it is limited to urban households in a limited number of provinces. As our objective is to estimate the national aggregate effect of income on energy consumption, we require observations from a more diverse set of households and cannot rely on this survey. Despite this, income elasticity estimates in Liang *et al.* (2014) are generally comparable to ours, although their estimates for heat and gas are considerably higher (and above unity). Golley & Meng (2012) use the same survey and document a strongly declining relationship between income and the direct household emissions intensity. They also combine survey data with input-output and emission coefficients, finding evidence for flat or even slightly increasing indirect emissions intensities (especially at high income levels). Other studies rely on aggregated data made available by the NBS for consumption across household types. Wei *et al.* (2007) for example document the relationship between energy use and lifestyles choices, but do not link them to income.

Growing recognition of the empirical relevance of non-homothetic preferences has prompted a number of studies to move to flexible demand systems where income elasticity is allowed not only to differ from one but to vary systematically with income (in line with the Generalized Engels Law, as defined by Matsuyama (2016)). For example, Li *et al.* (2015) estimate an Exact Affine Stone Index (EASI) implicit Marshallian demand system (Lewbel & Pendakur, 2009) and document high-rank non-linear Engel curves for several non-energy goods in China.

2.2 Data and Empirical Strategy

We begin with an overview of the data sets used and the procedure underlying our estimation of the income-consumption relationship. The central idea behind both the estimation and our projections is to use household income (and its projected growth) as a predictor of household consumption patterns. The data we rely on to estimate this relationship are purely cross-sectional, so using these estimates as we do for projection assumes that preferences are identical across Chinese households and stable over time.[2]

While we assume that households in all provinces will react in the same way to changes in income, expenditure shares are allowed to vary according to a number of covariates including cooling and heating degree days, household size, and prices. Our estimation also allows for differences in urban and rural household behavior. As our estimates are based on cross-sectional variation, they have a long-term interpretation: the underlying assumption is that households have had sufficient time to adapt all energy-consuming capital to their conditions (such as income, climate, or household size). Our methodology is thus best suited for mid- to long-term projection of consumption patterns, which is the primary focus of this exercise[3].

We estimate the relationship between income and consumption patterns separately for energy goods and non-energy goods. Consumption of energy goods, the main driver of results in this paper, is estimated using a household-level survey collected by Renmin University (Zheng *et al.*, 2014). Known as the China Residential Energy Consumption Survey (CRECS), the survey used to generate these data is based closely on the US Residential Energy Consumption Survey (EIA (Energy Information Administration, 2017). Household micro-data for China are scarce, and this energy-specific survey provides us with a detailed picture of the consumption of six types of energy goods $i \in I^{CRECS}$, which includes LPG, pipeline natural gas, gasoline and diesel, coal, central heating and

2 We are not aware of any sufficiently long panel data set that would enable us to test this assumption.

3 As our approach based on contemporaneous income and consumption decisions, it does not however explicitly account for lifetime income.

electricity by 4600 households $h \in H^{CRECS}$, representing a large income spectrum in both rural and urban areas and all provinces except for Tibet. **Figure 1** plots the geographical distribution of sampled households. The survey was administered between 2012 and 2014.

A significant share of household energy use is indirect, meaning that it is embodied in the consumption of non-energy goods. To capture the relationship between income and indirect energy use, we also estimate similar Engel curves for the eight aggregate consumption categories compiled by the Chinese National Bureau of Statistics (NBS) (the same as used in Wei *et al.* (2007) and Dai *et al.* (2011)[4]). While average consumption statistics are not an ideal substitute for household-level data, the data describe the large variation in consumption patterns and income captured by 420 different types of representative households that cover all provinces, seven income classes per province, and urban/rural types. The sectoral aggregation, while coarse, captures the observed shifts in consumption from agriculture and basic manufacturing towards services and transportation.

2.3 Estimation

To estimate the drivers of household energy consumption, we adjust each household h's nominal income I_{ihp} by the Stone price index to obtain a measure of real income which can be interpreted as 'implicit utility' in the Exact Affine Stone Index (EASI) demand system (Lewbel & Pendakur, 2009):

$$log\tilde{I}_{ihp} = \log I_{ihp} - \sum_i \theta_{ihp} \log P_{ip} - (1 - \sum_i \theta_{ihp}) \log CPI_p \,,$$

where P_{ip} represents the price of energy good i in Chinese province p and θ_{ihp} is good i's expenditure share. Price data for non-energy goods are unavailable and are approximated using consumer price indices for each province. As noted by Lewbel & Pendakur (2009), real income and nominal income are strongly correlated. Our main explanatory variable of interest is adjusted household income $\tilde{I}_{ihp}$, but we include a number of controls: household size HHS_{ihp} and, at the provincial level, cooling-and heating degree days, CDD_p and HDD_p, and an indicator for being within the regions north of the Huai river where heating is required and available, HZ_p. All of the controls are at least partially correlated with income. For instance, richer provinces have cheaper electricity prices (in real terms). Underlying our estimation of the relationship between income and household energy demand is a relationship between income and demand for energy services (cooking, heating, housing, transport, etc.). For our purposes, we do not separately estimate the determinants of energy services from those of actual energy use. For example, as households get richer, they might choose to live in a larger dwelling, which requires more energy to heat or cool. They might also choose to purchase a more energy-efficient heating or cooling system. We are only interested in the combined effect. Thus, we do not control for any household-specific characteristics such as dwelling size which may also be causally related to income. Given the small number of observations in some provinces, we do not include provincial fixed effects and simply pool our coefficients. Cross-provincial

4 These categories are: food, housing, transportation, medical, education, services, clothing, and furniture. This is the most detailed disaggregation available for all provinces and income classes. We use 2012 statistics. The NBS does not make the raw survey data available, and we are not aware of any detailed consumption survey that covers households in all provinces and levels of income.

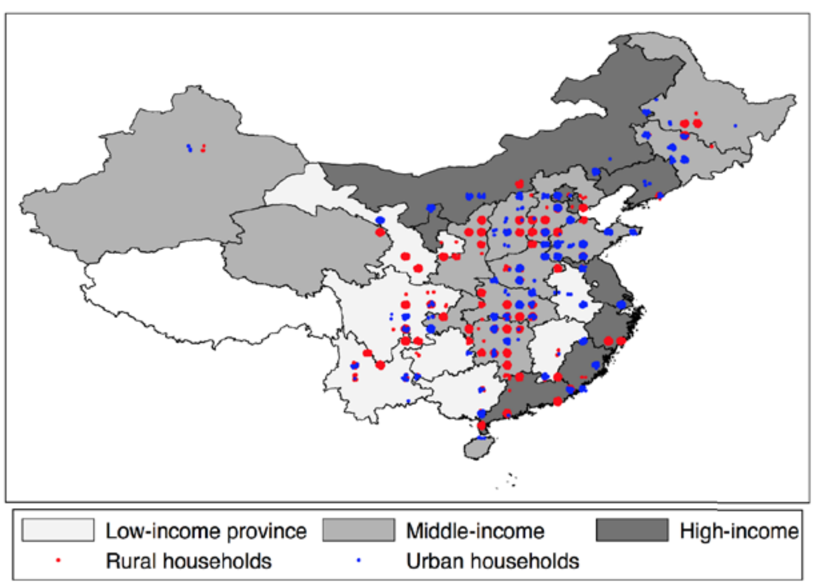

Figure 1. Geographical distribution of sampled households in household survey data (source: CRECS).

variation in energy demand is captured by temperature and prices.

The survey data include a large number of zero-consumption values, indicating that households do not necessarily consume all energy goods. We thus estimate the relationship between income and consumption in two steps, separately estimating first the adoption rates for each energy type and then the intensive margin of energy use. In both steps, we remain agnostic about the shape of the income-consumption function and estimate flexible functional forms, which will allow for intrapolation within the GE model. Equations used for the estimation are:

$$Pr(\theta_{ihp} > 0) = f^1(\tilde{I}_{ihp}) + g^1(CDD_p) + h^1(HDD_p) \quad (1)$$

$$\theta_{ihp} = f^2(\tilde{I}_{ihp}) + g^2(CDD_p) + h^2(HDD_p) + i^2(HZ_p) + j^2(HHS_{ihp}) + \sum_i \beta_i^2 \log P_{ip} + \epsilon^2_{ihp}, \quad (2)$$

where Equation (1) estimates the probability of adopting energy good i using a probit model. $\forall\, \theta_{ihp}$, Equation (2) estimates the conditional expenditure shares using OLS. ϵ^1_{ihp}, ϵ^2_{ihp} are residuals.[5] The equations are estimated for each good $i \in I^{CRECS}$ and for urban and rural households separately.[6] f (.), g(.), h(.) and i(.) represent higher-order polynomials, the best fitting combination of which is selected using the Akaike Information criterion (AIC). We allow polynomials of up to order six including log transformations and their polynomial transformations.[7]

The second step estimation of the intensive margin closely approximates the flexible EASI demand system, which allows for full-rank demand (see Lewbel & Pendakur, 2009) and is derived from utility-maximizing household behavior.[8] This flexible functional form embeds standard demand systems such as AIDS —if $\hat{f}(I_{ihp})$ is estimated as $\log(I_{ihp})$—or QUAIDS—if $\hat{f}(I_{ihp})$ is estimated as $\log(I_{ihp}) + (\log(I_{ihp}))^2$.

Income is found to be a significant determinant of demand for all goods at a significance level of at least p=0.01, except for coal consumption by urban households, for which there are very few observations. As is common in studies using household survey data to estimate demand systems, the R2 values are fairly low, ranging from 0.08 for gasoline adoption—associated with automobile ownership—to 0.53 for adoption of pipeline gas by urban households for step 1; and ranging from 0.06 for gasoline usage by rural households to 0.47 for coal usage by urban households for step 2. Using the estimates from Equations (1) and (2), we obtain the predicted probabilities of adoption for households of type $u \in$ {Urban, Rural}, $\hat{P}r(I)_{iu}$, and the predicted conditional expenditure shares for each good, $\hat{\theta}(I)_{iu}$, as functions of a given income level I. Combining them provides estimates of the predicted relationship between average expenditure and income (Engel curves):[9]

$$\hat{E}(I)_{iup} := \hat{P}r(I)_{iup}\, \hat{\theta}(I)_{iup}\, I\,. \quad (3)$$

These are displayed in **Figure 2**, evaluated at the mean of non-income covariates. We will refer to the average curves as $\hat{E}(I)_{iu}$. The figure shows that while the income-consumption paths are close to log-linear for some goods, non-linearity in most curves indicates that income elasticity usually varies with income. As noted by Gertler *et al.* (2016), estimated curves based on aggregated energy demand from multiple energy-using assets is not necessarily S-shaped. Our estimates imply relatively low income elasticities, except for gasoline and diesel and central heating (particularly for rural households). Coal consumption decreases with income—particularly for urban households—implying negative income elasticity. The same holds for bottled gas at high income levels.

5 The validity of our estimates depends on exogeneity of independent variables in both steps [$E(\epsilon^1_{ihp}X_{ihp}) = 0$ and $E(\epsilon^2_{ihp}X_{ihp}) = 0$]. Exogeneity is clear for the temperature-related variables and plausible for the price variables, as these vary by province and not by household and are largely the product of government-regulated pricing in China and therefore unlikely to depend directly on demand. Thus, the most critical assumption here is that energy consumption choices do not affect household income. Gertler *et al.* (2016) show that causality mainly goes from income to energy demand, suggesting that this assumption is reasonable. If energy usage did lead to larger incomes, our income elasticity estimates would be biased upward. Our findings imply low income elasticity. Correcting for endogeneity is expected to yield yet lower estimates.

6 Estimating the goods separately implies $E(\epsilon^1_{ihp}\epsilon_{i'hp}) = 0$] for all pairs of goods i and i^t. The large number of zero-consumption values prevent us from imposing cross-restrictions on the coefficients. However, Lewbel & Pendakur (2009) show that this is an acceptable approximation. Indeed, we find that the sum of the fitted values of the expenditure shares is very close to 1, even without the restriction, implying that the error terms are not significantly correlated across goods.

7 This is implemented using a multivariable fractional polynomial model that selects from all combinations of the variable and its log at powers -3, -2, -1, -0.5, 0.5, 1, 2 and 3.

8 Lewbel & Pendakur (2009) show that the EASI demand system can be closely approximated with a linearized ordinary least-squares estimation. Because of our two-step estimation procedure and the significant number of zero- consumption observations in our dataset, the exact structural estimation of EASI is not possible with these data .

9 We implicitly assume no sample selection issues and no link between the first and second step [$E(\epsilon^1_{ihp}\epsilon^2_{ihp}) = 0$]. We find evidence that unobserved variables may affect both steps, i.e. the residuals for both steps are found to be significantly correlated for most goods. This would be a problem if we were interested in the effect of income on consumption for those who consume a particular good. However, here we are focused on average expenditure by households at each given income level. Thus we are not concerned about sample selection problems in the classical sense.

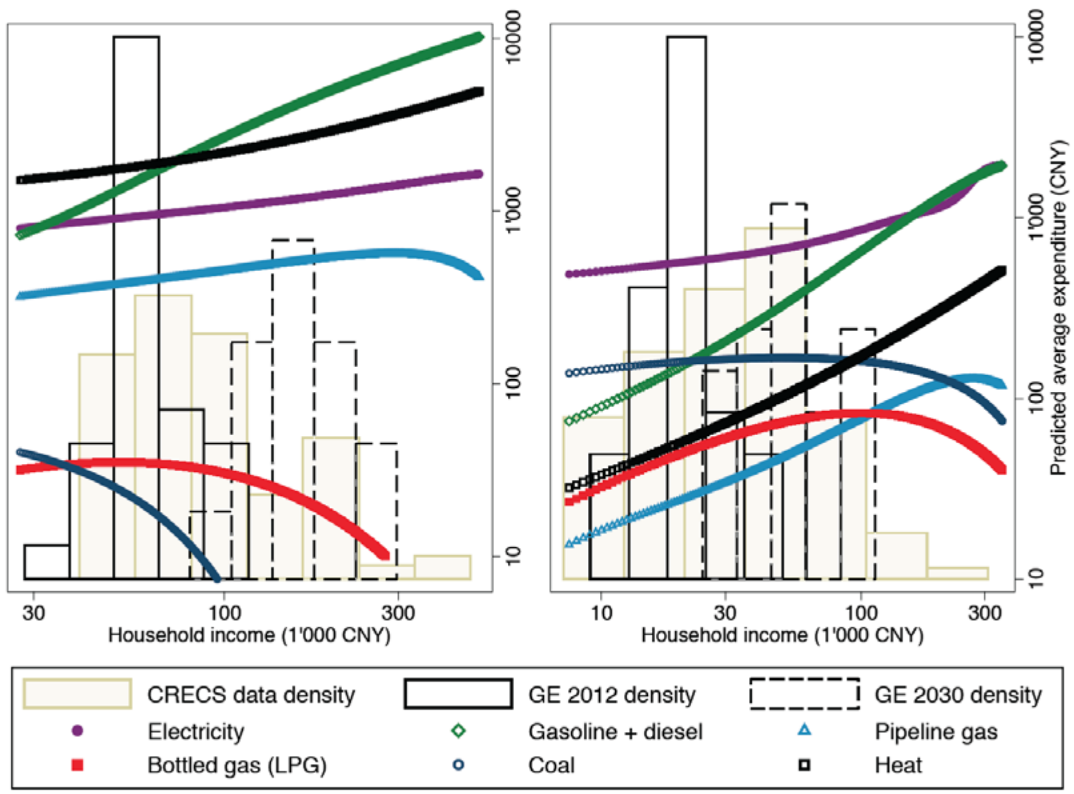

Figure 2. Estimated relationship between log household income and log energy expenditure (lines) and density of household incomes (histograms) for the sampled households from which estimates are derived (CRECS data density) and for households in the GE model for 2012 and 2030. Left panel: urban households; Right panel: rural households. Average expenditure is evaluated at the mean of the non-income covariates.

The large heterogeneity in observed income levels in the CRECS data allows our projections to be in-sample to 2030, as they cover a larger range of incomes than the projected average incomes in the general equilibrium model employed in our analysis.[10] We of course acknowledge that less is known about the expected behavior of the richest households and the prediction errors are anticipated to be larger at high incomes.

The Engel curve estimation for non-energy goods (based on NBS data) is similar to that of energy goods, albeit without the first step as we observe full adoption of each consumption category. We also do not control for cross-province price differences because price indices for these consumption categories are unavailable, however, evidence suggests that relative price differences between provinces are small. The variation in incomes provided by the NBS data, which describe seven income classes per province, also allows our projections for non-energy goods to be within-sample to 2030.

3. General Equilibrium Model

While the above estimated Engel curves could be combined directly with income growth projections to provide estimates of growth in energy demand, such an approach would implicitly assume perfectly elastic supply, exogenous income levels, and would abstract from demand for energy as an intermediate in production. It would thus not capture the feedbacks from changing consumption patterns on prices through a realistic representation of supply, and on income, through changes in returns to factors of production (including the resource rents that, combined with demand, determine energy prices). It would also abstract from feedbacks on investment and patterns of trade, which are—in addition to household consumption—important sources of emissions, especially in China where trade contributes a large share of GDP. The consequences of climate policy should be assessed

10 Average disposable household income in the model's base year (2007) ranges from CNY 68128 for urban households in Shanghai to CNY 5292 for rural households in Sichuan. Between 2007 and the final year in consideration (2030), real income levels increase by a factor that varies between 6.9 (Inner Mongolia) and 3.7 (Xinjiang), due to different provincial growth rates (Projected provincial income growth rates from 2007 to 2030 range from annualized values of 8.8% to 5.8%, with a national population-weighted average of 7.1%), bringing the highest household incomes in the model in 2030 to CNY 292072 (urban households in Guangdong).

within a framework that captures these effects. This motivates our use of a general equilibrium model.

3.1 Existing Energy-Economic Modeling Approaches

3.1.1 The Income-Consumption Relationship

Studies focused specifically on projecting future demand for energy services and associated emissions are widely based on aggregate macro data, which, in contrast to studies that use micro household data, do not identify the relationship between income and consumption and do not take patterns of adoption into account. Many studies are based on time-series or panel reduced form projections. For China for example, Crompton & Wu (2005) project future energy demand based on GDP, population and fuel prices. Auffhammer & Carson (2008) project Chinese emissions based on provincial-level data.

Numerous economic models used for energy and climate policy analysis assume that consumption scales proportionally with income, often for reasons of analytical or computational tractability and data limitations. Static analyses, including analytical general equilibrium models (Fullerton & Heutel, 2007; Fullerton & Monti, 2013) and computable general equilibrium models (Rausch *et al.*, 2011; Zhang *et al.*, 2013) hold production technologies and preferences constant when comparing outcomes in the presence and absence of policy. While instructive for developing intuition, these models are not designed to capture dynamics. Dynamic models (e.g., Goettle *et al.*, 2009; Rausch *et al.*, 2010a; Williams III *et al.*, 2015), by contrast, allow underlying features of the economy to evolve over time and interact with policy. These features, which are often empirically calibrated, include labor and capital productivity (Dai *et al.*, 2011), capital stock accumulation and depreciation (Goulder & Summers, 1989), autonomous rates of energy efficiency improvement (Webster *et al.*, 2008), and a rich representation of advanced technologies that can enter the market in response to policy (Jacoby *et al.*, 2006). Most efforts have focused on the supply side, with little attention given to household preferences.

The models that do implement non-unitary income elasticities usually do not use flexible demand systems, and while some employ energy-specific income elasticities, these are often based on simple calibration with no empirical basis or on values that are extrapolated from other sectors. The GTAP model (Hertel, 1997; Aguiar *et al.*, 2016), for instance, adopts the Constant Difference of Elasticities (CDE) demand system originally proposed by Hanoch (1975) and is calibrated to internally-consistent income elasticity estimates. These, however, are independent of the level of income and are estimated for broad consumption categories which do not separately identify energy. Other examples include MIT's EPPA model (Chen *et al.*, 2015), which calibrates Stone-Geary preferences to estimated income elasticities for the food and agricultural sectors only, the European Commission's GEM-E3 model (Capros *et al.*, 2013) which also calibrates Stone-Geary preferences to income-independent estimates,[11] and the World Bank's ENVISAGE model, which incorporates a more flexible demand system, AIDADS, but relies on elasticity parameters that are only estimated for broad consumption categories and lump energy with other consumption goods (and imply implausibly high income elasticities for energy[12]).

Finally, integrated assessment models (IAMs), which combine economic models with climate models and are used to evaluate climate change policies—and thus require the modeling of future energy use—typically describe the economy as a single sector. To the best of our knowledge, none of these models[13] explicitly allow for endogenous de-carbonization driven via shifts in consumption patterns (income-driven or not). In single-sector models, this mechanism is not otherwise distinguishable from supply-side determinants such as autonomous energy intensity improvements.

The present paper fills this gap by using micro data to estimate energy-specific income elasticities and integrate them within a general equilibrium economy-wide model. Our paper also contributes, to our knowledge, the first estimates of how income-dependent shifts in consumption patterns affect climate policy costs and incidence.

3.1.2 Household Heterogeneity

Most models used for the evaluation of environmental or energy policy represent the demand side of the economy using a single representative household. This convention abstracts from the many ways that household heterogeneity can affect aggregate economic outcomes and their dynamics. Variation in the rates of household income growth, for example, may interact with heterogeneous consumption patterns in determining the composition of total household consumption. This issue is exacerbated when preferences are non-homothetic (as the consensus in the literature suggests) and income levels vary widely across households.

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11 The authors do not document the source of the income elasticities they employ, but the virtual lack of variation of the estimates for most energy goods across a wide range of countries (see the table on p. 106 in Capros *et al.* (2013)) suggests that such estimates do not reflect relationships based on national-level household micro-data.

12 See Table A8.3 of van der Mensbrugghe (2010).

13 Examples of such models include the RICE/DICE (Nordhaus & Sztorc, 2013) model, Stanford's MERGE (Manne & Richels, 2004) model and FEEM's WITCH (Bosetti *et al.*, 2004) model.

The representative household approach also does not enable a consistent evaluation of the distribution of economic burden caused by policy. We build on recent work to incorporate heterogeneous households into general equilibrium models for incidence analysis (Rausch *et al.*, 2010a,b, 2011; Rausch & Schwarz, 2016), which allows us to distinguish how the impacts of policy are distributed across household types.

3.2 Model Features

Our general equilibrium modeling framework extends the China Regional and Energy Model (C-REM), a multi-region, multi-sector, recursive-dynamic global computable general equilibrium model with sub-national detail in China. Our model builds on Zhang *et al.* (2013) and Luo *et al.* (2016).[14] The model describes all 30 Chinese provinces, four international regions (the United States, Europe, other developing countries, and other developed countries), 13 sectors of the economy, including 5 energy goods and an energy-intensive industry sector, and 2 household types for the 2007 to 2030 period. The regional, sectoral and household aggregation scheme is shown in **Table C1** in the Appendix. The model satisfies standard neoclassical assumptions, with households maximizing welfare for given incomes (derived from factors of production, taxes and government transfers) at given consumption prices, firms maximizing profits in perfectly competitive markets, subject to government taxation, and a government raising taxes to meet its budget. Starting from a benchmark year, a set of technology assumptions, and a trajectory for labor productivity that determines GDP growth, the model solves for a series of equilibria at given time intervals.

Households are characterized by myopic expectations, and their behavior is thus optimal within, but not between, periods. Households are assumed to derive utility from savings, in addition to consumption and leisure. We do not consider the households preference for pollution (emissions) abatement.

Within time periods, household utility is represented as a nested function. At the top level, a Cobb-Douglas utility function describes substitution between consumption, leisure and savings. This generates a positive labor supply elasticity through the labor-leisure trade-off. At the lower level, utility from consumption is represented by a Stone-Geary function of the individual consumption goods. For household type $\bar{h} \in H$ in region $r \in R$ at time t utility from consumption is thus assumed to be of the following form:[15]

$$U_{\bar{h}rt}(\mathbf{x}) = \left[\sum_j \tilde{\theta}_{j\bar{h}rt} \left(\frac{x_j - c^{\star}_{j\bar{h}rt}}{x_{j\bar{h}rt_0} - c^{\star}_{j\bar{h}rt}} \right)^{\rho} \right]^{1/\rho}, \tag{4}$$

$$\tilde{\theta}_{j\bar{h}rt} = \frac{p_{jrt_0}(x_{j\bar{h}rt_0} - c^{\star}_{j\bar{h}rt})}{I_{\bar{h}rt_0} - \sum_{j'} p_{j'rt_0} c^{\star}_{j'\bar{h}rt}},$$

where $c^{\star}_{j\bar{h}rt}$ is the minimum level of required consumption of good $j \in J$ represented within the model, p_{jrt_0} the benchmark price, $x_{j\bar{h}rt_0}$ the benchmark consumption level, and $I_{\bar{h}rt_0}$ the benchmark income level, net of savings and leisure consumption. $\tilde{\theta}_{j\bar{h}rt}$ is the consumption share net of minimum consumption and ρ parametrizes the response of consumption to changes in relative prices.

Production of good j in region r (Y_{jr}) is assumed to exhibit constant returns to scale, with nested constant-elasticity-of-substitution (CES) functions representing differential substitution among inputs of intermediate goods (X_{jkr}), and productive factors capital (K_{jr}), labor (L_{jr}) and natural resources (R_{jr}), comprising land, fossil fuel, wind and hydropower resources:

$$Y_{jr} = F_{jr}\left(L_{jr}, K_{jr}, R_{jr}; X_{1jr}, \ldots, X_{Jjr}\right). \tag{5}$$

The nesting structure for each sectors' production function is expounded in Appendix C. Trade in goods and services is determined according to the Armington assumption of differentiated products by origin. Within China, labor is assumed to be mobile across sectors but not provinces, and capital is assumed to be mobile across both sectors and provinces. Outside China, both labor and capital are assumed to be immobile between regions. In both cases, natural resources are modeled as sector-specific factors.

Appendix C provides a detailed description of the economy's equilibrium conditions. The equilibrium is determined numerically by formulating a mixed complementarity problem (MCP) (Mathiesen, 1985; Rutherford, 1995), which is solved using the mathematical programming system MPSGE (Rutherford, 1999) and the PATH solver (Dirkse & Ferris, 1995).

Between periods, growth in region r's labor endowment ($\bar{L}_r$) is driven by the combination of population growth and labor productivity growth. Capital stock dynamics ($\bar{K}_{rt}$) are determined by the accumulation of new capital through investment ($Y_{INV,rt}$), which amounts to aggre-

14 Zhang *et al.* (2013) first presented the static version of C-REM, and Luo *et al.* (2016) developed a recursive-dynamic extension.

15 In the model, household utility from consumption is nested, as discussed in Appendix C . For simplicity, we abstract here from nesting.

gate household savings, and by the depreciation of existing capital:

$$\bar{L}_{rt_{l+1}} = (1 + g_{rt_l})^{t_{l+1}-t_l} \cdot \bar{L}_{rt_l} \tag{6}$$

$$\bar{K}_{rt_{l+1}} = S_{r,t_l} + (1 - \delta)^{t_{l+1}-t_l} \cdot \bar{K}_{rt_l} \, , \tag{7}$$

where δ is the depreciation rate, and g_{rt} is the sum of the population and the labor productivity growth rates.

Fossil fuel resources in each period are depleted to account for fossil fuel consumption in the previous period. Other sector-specific resources are assumed to grow at an exogenous rate. We furthermore assume energy efficiency to improve over time independently of changes in relative prices, through long-run autonomous energy efficiency improvement (AEEI) (Paltsev *et al.*, 2005).

3.3 Calibration

Starting from the base year (the calibration of which is described in Section 3.3.1 below), the economy's evolution is determined by recursively updating economic variables as described in Sections 3.3.2 and 3.3.3.

3.3.1 Base Year Calibration

Sub-national detail in China is parametrized using the set of 2007 provincial input-output tables and provincial energy balance tables made available by the National Bureau of Statistics of the People's Republic of China (NBS) (2008, 2011). Each province comprises a representative urban and rural household, $\bar{h} \in$ {Urban, Rural}, calibrated to provincial-level urban and rural consumption data. While household types likely also differ with respect to the sources from which they derive income, lack of data forces us to assume the composition of income for each household to be identical to the provincial average.

International regions are comprised of a single representative household. Economic and energy data as well as trade flows among all regions are parametrized using the GTAP (Global Trade Analysis Project) data base version 8 (Narayanan *et al.*, 2012).

Calibration of the substitution elasticities in the model's production functions is based on the MIT Emissions Projection and Policy Analysis (EPPA) model (Paltsev *et al.*, 2005): substitution between capital and labor is Cobb-Douglas; a value of 0.5 is assumed for both the elasticity of substitution between electricity and the fossil fuels composite, and between the value added and the energy composites in production. Following Caron *et al.* (2015), Armington trade elasticities are calibrated using estimates from GTAP, but the relative values of domestic and international elasticities are adjusted such that, in China, goods from other provinces are seen as closer substitutes to local (i.e. from within the province) goods than internationally sourced goods, which generates a border effect.

3.3.2 Dynamic Calibration

Starting from the base year 2007, we run our model to generate projections for 2010, 2015, 2020, 2025 and 2030.

The initial population growth rate in China is assumed to equal 0.5% per year (United Nations, 2011). The initial labor productivity growth rate is calibrated such that it reproduces observed provincial economic growth rates between 2007 and 2010. Similar to Paltsev *et al.* (2005), we then assume an S-shaped evolution from the initial growth rate to the long-term steady state:

$$g_{rt} = (g_{rt_0} - g_{rT}) \frac{1 + \alpha}{1 + \alpha e^{\beta(t - t_0)}} + g_{rT} \, , \tag{8}$$

where g_{rT} is the long-term (100 years) growth rate, assumed to be 2% per year. We set the values of α and β to 0.3 and 0.1. We assume the growth rate of land resources to be 2% per year. The savings rate is calibrated to base year data.

Physical energy quantities are obtained by province by first calibrating the model to observed economic growth, then adjusting energy efficiency to match 2010 observations for energy quantities based on National Bureau of Statistics of the People's Republic of China (NBS) (2012). The long-run autonomous energy efficiency improvement (AEEI) for all sectors is assumed to be approximately 2% per year in Chinese provinces (Cao & Ho, 2010) and about 1% per year outside of China. In order to isolate the role of changing household consumption patterns, we assume no energy efficiency improvements on the part of households.

3.3.3 Income-Dependent Consumption Patterns

Our main methodological contribution is an approach to capture income-dependent consumption patterns in a recursive-dynamic general equilibrium model, based on a hybrid demand system. The approach stems from the observation that changes in income in this class of models are primarily driven by productivity growth between periods whereas the within-period changes in income (due to energy or climate policies, for instance) are comparatively small. Allowing for flexibility in the shape of income-consumption relationships is thus most important for between-period changes. Our approach is furthermore based on the assumption that consumer behavior is myopic.[16] It allows us to calibrate the model to any empirically-estimated consumption path as a function of between-period changes in income. For a fixed set of relative prices, household expenditure shares follow the estimated Engel curves as income increases between periods. Within-period changes in income are captured by the Stone-

16 It should be noted that our approach would not be suited for rational expectations models, as in our framework preference parameters are updated between model periods, and are thus not fixed in time.

Geary demand system, which is appropriate for capturing the effect of comparatively small changes in income.[17]

For households within China, we proceed as follows.[18] First, we obtain the income of households of type u in province p at time $t(I_{upt})$ at benchmark prices, net of savings and demand for leisure. For this, we run the model with homothetic preferences (i.e., with minimum consumption parameters $c^{\star}_{jupt}$ set to zero), and divide nominal income levels by each consumer's price index.

Second, we project consumption at benchmark prices for each good j, time t, household type u and province p, in order to follow the estimated income-expenditure relationships. The aggregation of goods in the GE model differs from that of the data used for estimation described in Section 2. As is usually the case, aggregation schemes from input-output tables do not match those of consumption data derived from household surveys. We thus map the relationships between income and expenditure estimated in Equation (3) ($\hat{E}(I)_{ju}$) to corresponding relationships for goods in the GE model ($\hat{E}(I)_{ju}$). Some goods in the model are composites of goods used for the estimation.

The Engel curve for natural gas (GAS), for example, is constructed by aggregating the estimated curves for bottled gas (LPG) and pipeline natural gas. Other goods in the model map directly, such as the agricultural sector (AGR), for which the Engel curve corresponds to the estimated curve for food.[19]

We use the Engel curves $\hat{E}(I)_{ju}$ to look up the expenditures corresponding to the level of household income: $\hat{E}(I_{upt})_{ju}$. We then compute the proportional change in consumption for each good, and scale the level of benchmark consumption, x_{jupt_0}, by this factor. This delivers the demand projections y_{jupt} at benchmark prices:

$$y_{jupt} = \frac{\hat{E}(I_{upt})_{ju}}{\hat{E}(I_{upt_0})_{ju}} x_{jupt_0} \,. \tag{9}$$

17 Chen *et al.* (2015) also employ an iterative calibration procedure for Stone-Geary preferences. Our approach, however, differs significantly, as we target flexible Engel curves (which could be based on any functional form), rather than point estimates of income elasticities, and we account for the effect of the preference calibration on real household income levels. The scope of our application also differs greatly, as we target a wide range of goods, while (Chen *et al.*, 2015) calibrate income elasticities for food and agricultural products only.

18 Outside China, preferences are assumed to be homothetic. The corresponding minimum consumption levels are thus assumed to be zero (i.e., $c^{\star}_{j\hbar rt}$ for all regions r outside China).

19 There are some sectors for which we cannot construct a corresponding Engel curve based on our estimates. This concerns four of the twelve goods in the GE model which are primarily used as intermediate goods (CRU, OMN, EIS and WTR). For these goods, household consumption is very small and we assume it to scale in proportion to income.

Third, we calibrate consumer preferences such that at the level of income I_{upt} and benchmark prices, consumption for each good j is equal to the projected (empirically-grounded) level y_{jupt}. The proposition below shows that Stone-Geary preferences can indeed be calibrated in this way.

Proposition. Assume $t > t_0$. The following calibration ensures that at benchmark prices and at the income prevailing at time t, I_{upt}, the consumption of each good corresponds to the projections based on the estimated Engel curves, y_{jupt}:

$$c^{\star}_{jupt} = \left(x_{jupt_0}\frac{I_{upt}}{I_{upt_0}} - y_{jupt}\right)\left(\frac{I_{upt}}{I_{upt_0}} - 1\right)^{-1} . \tag{10}$$

Proof. At benchmark prices, the demand function for good j by household u in province p at time t is given by

$$x_{jupt}(\mathbf{p}_{rt_0}, I) = (x_{jupt_0} - c^{\star}_{jupt})\frac{I - \sum_{j'} p_{j'pt_0}c^{\star}_{j'upt}}{I_{upt_0} - \sum_{j'} p_{j'pt_0}c^{\star}_{j'upt}} + c^{\star}_{jupt} \tag{11}$$

Since $\sum_j p_{jpt_0} y_{jupt} = I_{upt}$, the following holds for the $c^{\star}_{jupt}$, from (10): $\sum_j p_{jpt_0} c^{\star}_{jupt} = 0$. For this calibration, the subsistence consumption parameters at benchmark prices sum to zero in any given period, since household expenditure across all goods equals income. We use this to simplify Equation (11):

$$\begin{aligned} x_{jupt}(\mathbf{p}_{pt_0}, I \equiv I_{upt}) &= (x_{jupt_0} - c^{\star}_{jupt})\tfrac{I_{upt}}{I_{upt_0}} \\ &+ c^{\star}_{jupt} = x_{jupt_0}\tfrac{I_{upt}}{I_{upt_0}} + c^{\star}_{jupt}(1 - \tfrac{I_{upt}}{I_{upt_0}}) \end{aligned}$$

then insert Equation (10), thus obtaining the following equality: $x_{jupt}(p_{pt_0}, I \equiv I_{upt}) = y_{jupt}$

Fourth, we run the model with the newly calibrated preferences, obtaining new real income levels I'_{upt}. These are not generally equal to initial income (i.e., $I'_{upt} \neq I_{upt}$), both because the same prices and nominal income levels correspond to different levels of real income for different utility functions, and because different preferences will lead to a different market equilibrium, influencing prices and income. We therefore re-calibrate household preferences following steps two and three above, and re-run the model iteratively until real income has converged.[20] The resulting preferences are such that, at the levels of real income at a given time t and for benchmark prices, consumption levels correspond exactly to the projections based on the estimated Engel curves.

The use of Stone-Geary preferences in our hybrid approach is motivated by the fact that implementation within a general equilibrium model is simple and deliv-

20 Convergence in our specific case is achieved after four iterations, as detailed in Appendix A.

ers an approximation of the local properties of the Engel curve estimates. Additionally, since proportional changes in utility levels are equivalent—in welfare terms—to proportional changes in income at benchmark prices[21] (as our calibration ensures that $\sum_j p_{jpt_0} c^{\star}_{jupt} = 0$), our approach provides a metric to consistently evaluate the welfare impact of policy shocks across periods.

4. Baseline Projection

We first summarize the effect of income-driven changes in consumption patterns on baseline projections of economic activity, energy use, and emissions. In order to isolate the role of these changes, we compare the results for calibrated non-homothetic preferences (which we will refer to as the *Calibrated* case) and the results for an alternative counterfactual case in which preferences are assumed to be homothetic.[22] We refer to this counterfactual as the *Proportional* case, since homothetic preferences imply proportional income-consumption relationships for all goods.

4.1 Composition of Household Consumption

Table 1 displays the composition of household consumption at the national level, both in the base year and in the final year of our simulation, 2030. In the proportional case, the average expenditure shares on energy goods as well as on agricultural goods increase over time. This indicates that the effect of rising energy prices, driven by the depletion of fossil fuel reserves, and rising agricultural goods prices, caused by the relative scarcity of land, outweighs the effect of substitution away from these increasingly expensive goods. Accounting for the empirically calibrated income-expenditure relationships reverses this trend, both for agricultural goods as well as for all energy goods with the exception of oil. While the average consumption share of oil in the final year is higher than in the base year, it is nonetheless lower than in the proportional baseline. Noteworthy for models that capture only price effects, our results illustrate that income-driven shifts away from energy and agricultural goods have a stronger effect on consumption patterns than price-driven effects, due to the low income elasticities for these goods and the rapid growth in household income levels.

Manufacturing, transportation, and services represent a roughly constant share of average household consumption under homothetic preferences, as they see modest fluctuations in prices. However, the calibrated non-homothetic preference projection shows manufacturing shrinking in relative importance within household consumption baskets, while the average share of services strongly increases and that of transportation more than doubles.

Table 1 also shows that in the proportional case, the standard deviation (across provinces and household types) of the expenditure shares of energy and agricultural goods increase in time, as differences between households are magnified by the increase in prices, while for other goods the values are roughly constant. The variation in household expenditure shares thus increases on average, suggesting divergence in relative consumption baskets across households.

The story is different in the calibrated case: the standard deviation in expenditure shares is lower for most goods, with the notable exception of transportation and services. It is therefore not clear *a priori* if changes in the composition of consumption driven by rising incomes will lead to a divergence or a convergence in the energy and emissions-intensity of consumption baskets and therefore in the distribution of welfare impacts caused by climate policy-driven changes in relative prices. We investigate this question later in the paper.

4.2 Energy Use and Emissions

Table 2 displays China's demand for each energy type, in 2007 and in 2030, for both the calibrated and proportional cases. In the calibrated case, direct household demand for energy is dramatically reduced compared to the proportional case. The relative reduction in total national demand for energy is smaller since household demand for energy only represents a fraction of national demand, which also includes intermediate demand (a substantial part of which goes to exports), government, and investment demand, all of which are particularly high in China.

Total household consumption of coal in 2030 is projected to be lower than its base year value, as expected given that its Engel curve estimates suggest it to be an inferior good for all but the poorest rural households, and is 81% lower compared to projected consumption in 2030 with homothetic preferences. The least affected energy good, refined oil, sees its household demand reduced by approximately 5% relative to the baseline projection. Overall, household demand for energy in 2030 is 58% lower than in the proportional case. National energy demand is 6% lower.

Changes in household energy demand by type between the proportional and calibrated cases do not translate directly to changes in national demand because of a number of general equilibrium effects.

21 Equivalently, proportional changes in utility levels correspond to the equivalent variation at benchmark prices, divided by benchmark income.

22 This corresponds to the case with minimum consumption parameters $c^{\star}_{j\bar{h}rt}$ set to zero, implying within-period CES preferences calibrated to shares that remain unchanged between periods.

First, lower demand on the part of households depresses prices for most energy goods, causing an increase in the intermediate demand from the other sectors (which use energy goods as inputs). This mitigates the effect of income-driven consumption shifts. Exports are also affected, but to a lesser extent.

Second, changes in demand for non-energy goods affect demand for energy goods as production inputs. In addition to direct household use in privately-owned vehicles, refined oil is an input to purchased ground and air transportation, which experiences a doubling in its share of household consumption between 2007 and 2030. Although direct household demand for oil is slightly reduced by the consumption shift relative to the proportional case, the national demand for oil is higher due to higher indirect household demand. This is also reflected in the price of oil, which increases slightly in the calibrated case.

Changes in the household consumption of energy and non-energy goods affect the levels of CO_2 emissions in the Chinese economy, both directly through emissions caused by the burning of fossil fuels and the consumption of electricity at the household level[23], and indirectly through changes in the composition of production to satisfy changing consumer preferences for non-energy goods. **Table 3** summarizes these changes. In 2030, direct household CO_2 emissions are lower by 1.67 billion tons as a result of reduced household consumption of fossil fuels and electricity, a 61% reduction compared to the homothetic case. National CO_2 emissions in the final year are roughly 8% lower compared to the proportional case, corresponding to a reduction of 1.22 billion tons of CO_2 emissions—an amount just slightly larger than Japan's emissions in 2011. We note also that the difference between direct household and total emissions, explained by the important shares of government, investment and export-related emissions, are exceptionally large in China (and that household emissions likely have a greater influence on total emissions in most other countries).

23 We follow most of the literature here and include electricity-related emissions in direct household emissions.

5. Policy Analysis

We now study the interaction between income-driven changes in the composition of household consumption and climate policy. We design a simple stylized policy which reflects current policy proposals. We consider a set of national CO_2 emissions targets, implemented by an economy-wide national CO_2 price. As above, we compare the outcomes of the proportional and calibrated cases under this policy.

By design, we choose emissions levels under policy to be identical in both cases. This allows a direct comparison of the costs of achieving a fixed environmental outcome. Since baseline emissions are lower in the calibrated case, the absolute emissions reductions will be lower than with homothetic preferences. Income-driven shifts in the composition of household consumption thus directly affect the stringency of the climate policy.

Figure 3 illustrates baseline emissions for the calibrated and proportional cases, as well as the targeted emissions

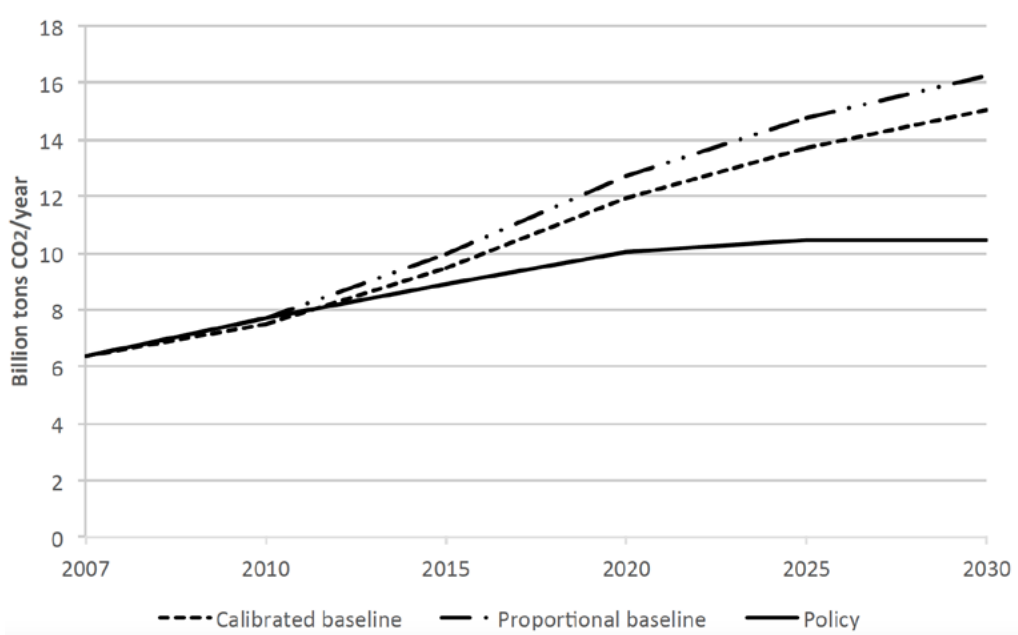


Figure 3. National CO_2 emissions for baseline and policy, for homothetic and for non-homothetic preferences.

Table 1. Baseline household expenditure share by good (% of total consumption)

	Average			Standard deviation		
	2007	2030		2007	2030	
Preferences:		Proportional	Calibrated		Proportional	Calibrated
COL	1.0	1.4	0.3	1.1	1.6	0.5
GAS	0.2	0.3	0.1	0.4	0.6	0.2
OIL	2.1	3.1	2.9	1.6	2.5	2.3
ELE	3.4	3.5	1.2	2.1	2.2	0.8
AGR	15.3	17.2	12.6	8.6	9.4	7.7
MAN	32.1	31.0	24.4	8.5	8.3	7.0
TRN	2.6	2.6	6.1	1.2	1.2	2.9
SER	35.6	33.7	43.6	8.5	8.5	9.8

Notes: Averages and standard deviations computed across provinces and household types (urban/rural), weighted by population.

Table 2. Baseline national and household-level demand for (secondary) energy by energy type

	Quantity								Price index		
	Household demand				National demand						
	2007	2030			2007	2030			2030		
Prefs.:		Prop.	Calib.	Diff.		Prop.	Calib.	Diff.	Prop.	Calib.	Diff.
COL	77	303	58	-81.0%	836	2332	2215	-5.0%	1.57	1.43	-8.5%
GAS	15	69	24	-65.2%	72	292	259	-11.4%	1.13	1.05	-6.7%
OIL	46	180	170	-5.5%	504	1183	1209	+2.2%	1.72	1.73	+0.6%
ELE	73	366	135	-63.1%	519	1816	1599	-12.0%	0.91	0.88	-3.0%

Notes: Units: Mtce (Quantity); prices relative to 2007 levels (Price index). Note that COL, GAS, and OIL data excludes demand from the electricity sector for these inputs to avoid double counting. Price index constructed as an average of regional prices relative to benchmark, weighted by provincial energy consumption for each energy type.

Table 3. Baseline national and household-level emissions (Billion tons CO_2/year)

	Direct household emissions			National emissions		
Preferences:	Proportional	Calibrated	Difference	Proportional	Calibrated	Difference
2007	0.8	0.8	0.0%	6.4	6.4	0.0%
2010	1.0	0.8	-19.7%	7.7	7.5	-2.3%
2015	1.4	0.8	-38.4%	10.0	9.5	-4.9%
2020	1.9	0.9	-50.1%	12.7	11.9	-6.4%
2025	2.3	1.0	-56.5%	14.8	13.7	-7.2%
2030	2.7	1.1	-60.8 %	16.3	15.0	-7.5%

Notes: Direct household emissions comprise emissions from the domestic combustion of fossil fuels, as well as the emissions embodied in electricity consumed by households.

path under policy. The CO_2 emissions targets (displayed in **Table 4** as *Emissions targets*) correspond to an emissions trajectory that results from simulating a 4% yearly reduction in CO_2 intensity in the proportional case, consistent with current target emissions paths aiming to achieve a CO_2 emissions plateau by 2030 (Zhang *et al.*, 2016b). This policy only targets fossil fuel-based CO_2 emissions, such that the results of the following sections can be considered similar to those of a policy that targets energy use (associated with other externalities such as local air pollution) directly.

The allocation of the revenues generated by carbon pricing has important consequences for incidence. In our analysis, unless specified otherwise, we consider a redistribution scheme in which the revenue is returned to households in each province in lump sums proportional to baseline income. Such revenue recycling does not affect the distribution of income, shutting off this channel of incidence and keeping the focus on the impact of differences in household preferences on welfare.

5.1 Energy Use and Emissions Reductions, Carbon Prices, and Average Policy Impacts

The policy significantly affects energy use, as can be seen from **Figure 4**. Focusing on the results for calibrated preferences, we find that primary energy demand in 2030 is reduced by 28% relative to the baseline. Under the policy, coal use peaks around 2025, while energy consumption from oil, gas and renewable sources continues to increase, albeit from a smaller base. By comparing the 28% reduction in primary energy to the 30% reduction in CO_2 emissions in the policy against the baseline projection, we find that substitution away from energy use rather than substitution among energy sources is the main driving factor in the overall reduction of carbon emissions in our simulations.

Table 4 reports the effect of climate policy on national emissions, as well as the associated carbon price and policy impacts. Importantly, the reduced stringency of policy under calibrated preferences, due to the lower base-

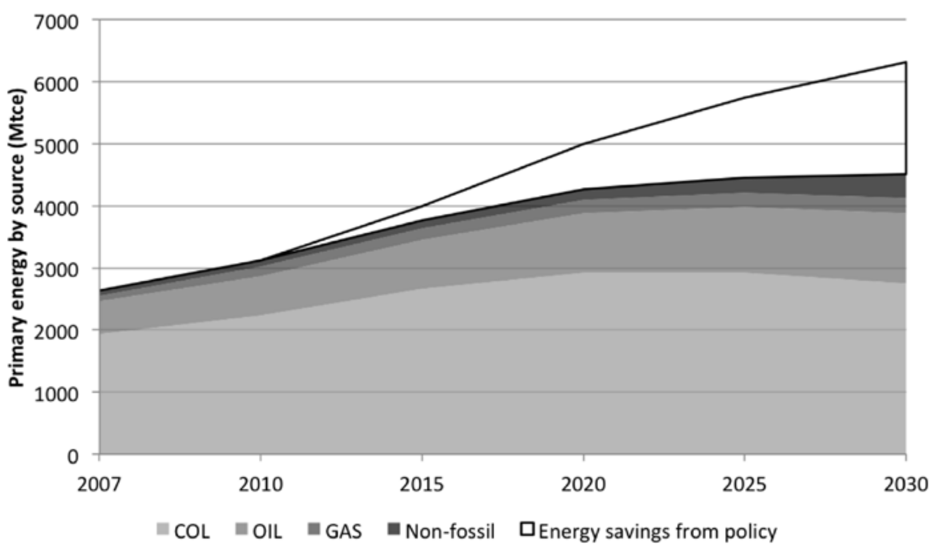


Figure 4. Primary energy by energy source for calibrated preferences under policy.

Table 4. The effect of climate policy on national emissions, the associated carbon price, average consumption loss and average provincial GDP loss: comparison of calibrated non-homothetic (calib.) and proportional homothetic (prop.) preferences.

	Emissions					Policy impacts			
	Targets	Reductions		Price		Consumption loss		Provincial GDP loss	
Prefs.:		**Calib.**	**Prop.**	**Calib.**	**Prop.**	**Calib.**	**Prop.**	**Calib.**	**Prop.**
2015	8.9	0.6	1.1	8.1	16.0	0.3%	0.9%	0.4%	0.7%
2020	10.0	1.9	2.7	26.9	42.7	1.1%	2.6%	1.4%	1.8%
2025	10.4	3.3	4.3	49.5	74.3	2.0%	4.6%	2.6%	3.1%
2030	10.5	4.6	5.8	72.7	111.7	2.9%	6.3%	3.5%	3.9%

Notes: Units: Emissions: Billion tons CO_2/year. Price: USD per ton of CO_2. Averages are weighted by population. Here and elsewhere in the paper, an exchange rate of 7.6 CNY per USD has been applied (2007 average).

line emissions, translates to a 35% lower carbon price[24] in 2030. We measure welfare impacts (expressed as equivalent variation relative to real income) in terms of changes in welfare from consumption and will thus also simply refer to it as *consumption loss*.[25] Assuming a 4% annual discount rate, the net present value of the total consumption loss to 2030, accounting for the recycled revenue, amounts to 395 billion 2007 USD for the calibrated case. Cumulative emissions reductions amount to 43 billion tons of CO_2. The average welfare cost thus amounts to 9.2 USD per ton abated. In the proportional case, the cost is 17.8 USD per ton abated, reflecting rapidly increasing marginal abatement costs.[26]

The average provincial consumption and GDP losses under policy, for each period following the implementation of the policy, as reported in Table 4[27], show that ignoring income-driven shifts substantially overestimates the average costs of reaching a given emissions trajectory: higher baseline emissions in the proportional case lead to an implicitly more stringent and therefore more costly policy. The estimated Engel curves thus imply that income growth drives a shift away from energy goods and reduces the CO_2 intensity of household consumption, such that households are less exposed to the carbon price. It is important to note that welfare costs in the proportional case are more strongly overestimated compared to GDP costs: the consumption shift has a larger mitigating effect on the CO_2 intensity of household consumption than on other components of GDP, so the CO_2 price generates larger differences between the calibrated and proportional cases in household consumer price indices than in the economy-wide price index. As a consequence, nominal income losses translate into larger differences in welfare compared to GDP.[28] This is important because household welfare, not GDP, should arguably be the metric of greater interest to policy makers.

5.2 Distributional Impacts of Policy

We now focus on the policy's distribution of impacts across household types, defined here by province and urban/rural status. We start by describing the distribution of welfare impacts. Section 5.2.1 will then highlight the drivers of these results, based on a welfare decomposition. Section 5.2.4 will finally identify the reasons for the differences in the distributional results between calibrated and proportional cases.

We first describe the distribution of welfare impacts by pooling households into subgroups, allowing differentiation along various policy-relevant dimensions. We focus first on average consumption loss within subgroups in the calibrated preferences case. We then compare results to outcomes with homothetic preferences (proportional case). Results are displayed in **Table 5**.

Under our assumption of income-proportional redistribution of CO_2 pricing revenues, we find that rural households are on average more negatively affected than urban households; households in low income provinces are more affected than households in medium and high income provinces (as can also be seen for average provincial-level impacts in the left panel of **Figure 5**); households in provinces with high coal production are more affected than households in provinces with low coal production. From the right panel of Figure 5, we can also see that households in provinces with a high carbon intensity of GDP are impacted more strongly. The geographic distribution of impacts also varies widely (as can also be seen from **Figure 6**): Western provinces suffer the most, Eastern provinces the least, with Central provinces (with the exception of Shanxi, a major coal producer and exporter, which is highly affected) falling in between.

As an aside, we also investigate sensitivity to redistributing the CO_2 price revenue proportional to provincial emissions rather than household income. Results are reported in the middle columns of Table 5. The difference in welfare impacts between relative winners and losers generally decreases, as provinces with high emissions intensity of GDP, which tend to be more negatively affected by the policy, benefit from a higher share of revenues from the carbon price.

24 This is the shadow price of the model's carbon constraint.

25 We report the loss in utility from consumption rather than loss in total utility, which in the model also includes utility from leisure and savings. These are introduced into utility to generate positive within-period labor and capital supply elasticities, and their contribution to welfare is thus arbitrary. Another possible measure of household welfare would include government expenditures. We find that both the patterns of incidence and the effect of our preference calibration on the distribution of impacts reported in the following sections are robust to the use of such alternative measures of household welfare.

26 For comparison, Rausch & Karplus (2014), also using a 4% discount rate, find for the US that cumulative CO_2 reductions of 50 billion tons by 2050 result in 2005 net present welfare costs of approximately 5 USD per ton. For 100 billion tons of cumulative reductions, they find welfare costs of roughly 15 USD per ton.

27 Both the consumption loss and the average provincial GDP loss are weighted by population. We consider average provincial GDP loss rather than national GDP loss, in order to make it more comparable with the loss in house- hold welfare from consumption. Since household incomes differ across provinces and household types, population weighted % changes differ from the % changes in the totals.

28 It should be noted that this would still hold if household consumption were also subject to an AEEI, as the consumption shift would still have a much larger mitigating effect on the CO_2 intensity of household consumption than on the average intensity of GDP. This would also hold if the economy-wide AEEI were zero. The quantitative results in these two alternate cases would, naturally, differ.

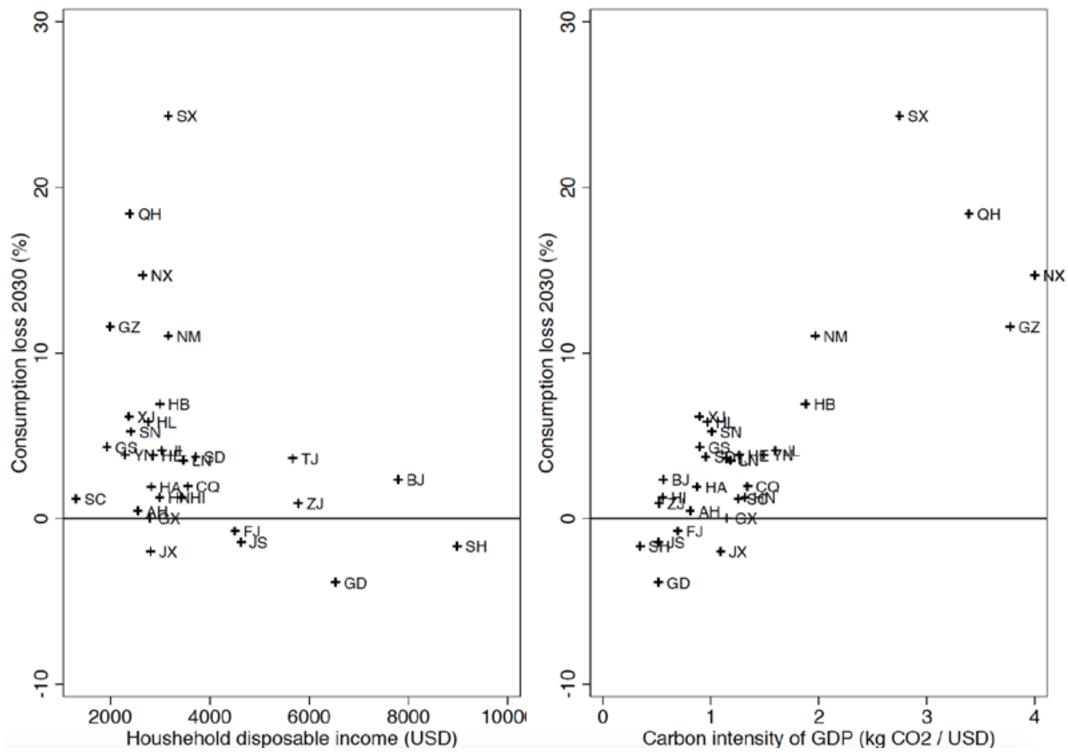


Figure 5. Relationship between consumption loss in 2030 and base-year household disposable income / carbon intensity of GDP for calibrated preferences and income-proportional revenue redistribution.

Table 5. % consumption loss with respect to the baseline for calibrated non-homothetic versus proportional pref- erences and alternative redistribution schemes of revenues from CO_2 pricing, population-weighted average values (standard deviations in brackets), with households divided into subsets

Preferences:	**Calibrated**				**Proportional**	
Redistribution:	**Income-proportional**		**Emission-proportional**		**Income-proportional**	
	2015	**2030**	**2015**	**2030**	**2015**	**2030**
All households	0.3	2.9	0.3	2.6	0.9	6.3
	(1.0)	(5.1)	(0.5)	(2.9)	(2.0)	(8.1)
Urban	0.2	2.3	0.1	2.2	0.7	5.0
Rural	0.4	3.4	0.4	3.0	1.2	7.5
East	0.0	0.7	0.0	0.7	0.3	2.9
Central	0.6	4.6	0.5	4.2	1.5	9.0
Central*	0.3	2.9	0.4	3.5	0.9	6.7
West	0.5	4.1	0.4	3.5	1.3	8.2
Low coal production	-0.3	0.0	0.0	1.9	-0.4	0.9
Medium coal production	0.3	2.8	0.2	2.2	1.0	6.6
High coal production	2.7	15.9	1.5	9.3	5.8	26.8
High income	0.1	1.9	0.1	2.0	0.5	4.4
Medium income	0.2	2.2	0.1	1.8	0.8	5.5
Low income	0.6	4.5	0.5	4.1	1.5	9.0

Notes: Coal production: High (above 5 % value of base year output from COL), Low (below 1 % value of base year output from COL). Eastern provinces: BJ, FJ, GD, HI, HE, JS, LN, SD, SH, TJ, ZJ; Central provinces: AH, HL, HA, HN, HB, JX, JL, NM, SX; Western provinces: CQ, GS, GX, GZ, NX, QH, SN, SC, XJ, YN. Central*: without SX.

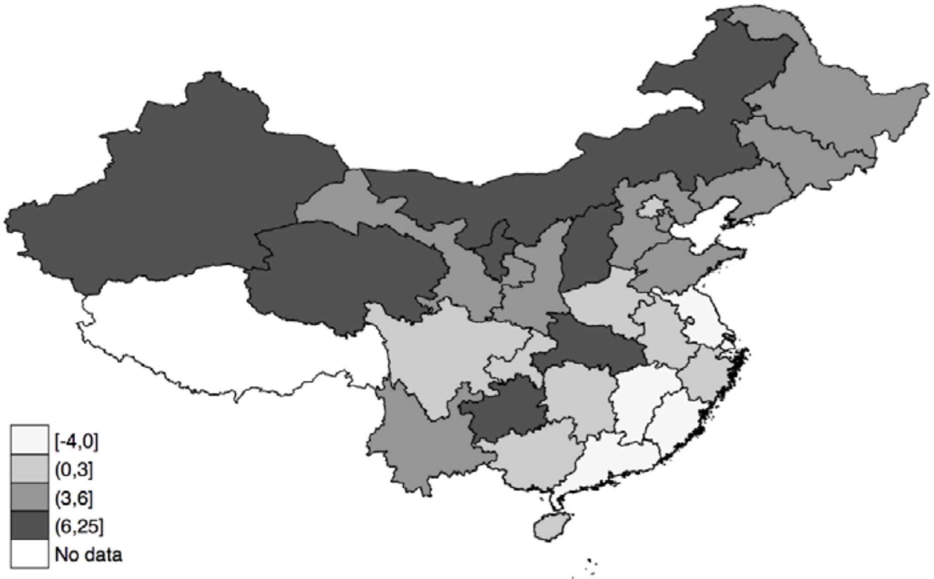
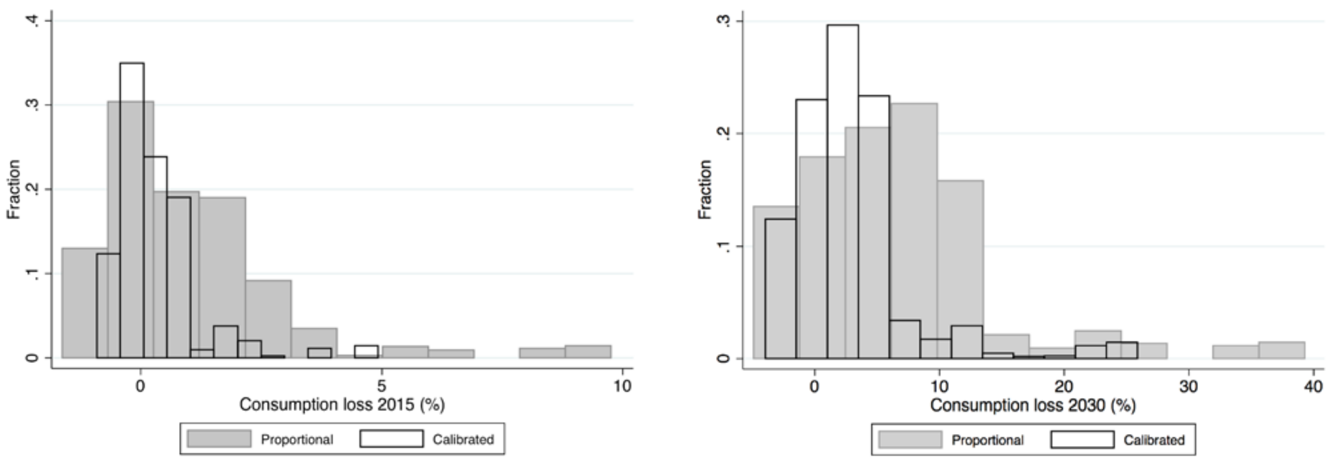


Figure 6. Geographic distribution of % consumption loss in 2030 for calibrated preferences and income-proportional revenue redistribution.



(a) 2015

(b) 2030

Figure 7. Population-weighted distribution of welfare impacts (across provinces and urban/rural types) of policy for calibrated and proportional preferences.

Compared to calibrated preferences, average consumption losses in the proportional case are more pronounced in almost all of the subgroups considered. Importantly, the difference in impacts among subgroups is also larger. As an example, low income households in the calibrated case suffer consumption loss which is 2.6% higher than high income households in 2030 (4.5% against 1.9%) instead of 4.6% in the proportional case.

Turning to the distribution of these losses across all households, as can be seen on the second line of Table 5, standard deviations increase in time in all cases, as the increasing stringency of the climate policy magnifies relative differences among household types and provinces. For a given year, the variation of impacts is reduced under the emissions-based allocation of carbon price revenues, confirming that this alternative redistribution scheme is more neutral. Standard deviations in the calibrated case are lower than in the proportional case, implying that—compared to an incidence analysis that would abstract from the income-driven consumption shifts—the variation of welfare impacts is lower.

Figure 7 displays the impacts of policy across the full set of urban and rural representative households for all provinces, in 2015 and 2030. In both years, under calibrated preferences, the figure shows that the average consumption loss is not only lower, but that losses exhibit less variation across subgroups. The following sections further unpack these results.

5.2.1 Decomposing Variation in Welfare Impacts

The welfare results displayed so far are general equilibrium estimates and correspond to the equivalent variation associated with changes in utility from consumption, relative to real baseline income. In order to identify the drivers of variation in welfare impacts, we perform an ex post decomposition which approximates equivalent variation using the change in consumer surplus caused by changes in prices, quantities consumed and income, as in West & Williams III (2004). We then measure the contribution of each of these components to the variation in impacts across households under both preference calibrations.

Similarly to Williams III *et al.* (2015), we assume the demand curve to be linear in the relevant range such that the change in consumer surplus relative to income is given by:

$$\frac{\Delta S}{I} = \underbrace{-\sum_j \frac{\Delta p_j}{p_j}\theta_j}_{=\textit{First order consumption}} \underbrace{-\frac{1}{2}\sum_j \frac{\Delta p_j}{p_j}\frac{\Delta x_j}{x_j}\theta_j}_{=\textit{Second order consumption}} + \underbrace{\frac{\Delta I}{I}}_{=\textit{Income}} \cdot \quad (12)$$

where province and household indices are suppressed for simplicity, $\Delta I = I^{Policy} - I$, with I the baseline income (net of savings and leisure consumption) and I^{Policy} the income under the policy, $\theta_j = \frac{p_j x_j}{I}$ the baseline expenditure share on good j, $\frac{\Delta p_j}{p_j}$ the proportional change in the price of good i and $\frac{\Delta x_j}{x_j}$ the proportional change in the consumption of good j.[29] We find that the change in consumer surplus from Equation (12) delivers a good approximation of the general equilibrium estimates of equivalent variation, for the proportional as well as the calibrated case.[30]

The first two terms on the right-hand side of Equation (12) vary across households because of policy-driven changes in relative consumption good prices. We refer to these two terms as capturing "consumption side" impacts. The third term varies because of differing proportional changes in income. We refer to this term as reflecting "income side" impacts. It should be noted that this decomposition does not allow a comparison of the relative magnitude of consumption and income side impacts at the household level, which is not pinned down and depends on the choice of the numeraire (Fullerton & Metcalf, 2002). It does, however, capture differences within each term across households, which are not affected by the choice of the numeraire.

The distribution of the first "first-order consumption" term across households captures differences in welfare impacts caused by policy-induced changes in relative prices and differences in consumption patterns among households, holding consumption quantities and incomes constant. More precisely, this term reflects the within-household covariance between proportional price changes and expenditure shares across sectors: households that intensively consume goods experiencing large price increases under the policy will be more adversely affected. If the price changes were the same in all provinces, and if all households were to consume goods with the same intensity (expenditure shares were equal across all households), then the variability in impacts through this channel would be zero.

The "second-order consumption" term captures second order effects that mitigate the first order term through changes in consumption caused by the policy: households can at least partially substitute away from consuming goods that experience a relative price increase.

The policy affects household incomes in many ways (among others through returns to factors of production and recycled carbon price revenue). Households in provinces where industry is particularly hard hit by policy will experience larger losses on the income side, through the decrease in the returns of their productive factors. Further decomposing the third "income side" term is, however, not the focus of our paper, as we are mainly interested in comparing variation in income-side effects to variation in consumption-side effects, under homothetic and non-homothetic preferences. Equation (12) thus highlights a number of channels through which income-driven consumption shifts may affect the distribution of welfare impacts: expenditure shares (θ), price changes under policy ($\frac{\Delta p}{p}$), income changes ($\frac{\Delta I}{I}$) and behavioral responses ($\frac{\Delta x}{x}$). We distinguish two types of effects. On the one hand, household expenditure shares differ between the calibrated and proportional cases. This will cause given changes in relative prices under policy to translate to different distributions of welfare impacts. We will refer to this as the *direct effect* of changing consumption patterns.

On the other hand, changing consumption patterns also have an *indirect effect* on the distribution of welfare impacts, through a number of channels. First, income-driven consumption shifts affect baseline emissions, and hence the absolute amount of emissions reduced by the policy. The differing stringency will in turn affect consumption good price and income changes under policy,

29 Similarly to Williams III *et al.* (2015) we normalize prices such that the average consumer price index, $p_{avg,t}$, remains constant. It is defined as: $p_{avg,t} := \sum_{jup} \frac{x_{jupt}}{\sum_{u'p'} I_{u'p't}} p_{jpt}$, where I_{upt} is the pre-policy income of household type u in province p at time t and x_{jupt} is the pre-policy consumption of good j.

30 This can be seen in **Figure B1** in the Appendix.

through the (here, lower) economy-wide CO_2 price. Second, even abstracting from differences in policy stringency, non-homothetic preferences affect equilibrium good and factor prices through differing patterns of demand, and thus production, compared to the homothetic case.

Whereas the direct effect affects the consumption channel only, the indirect effect affects both the consumption and the income channel. We now tease out the relative importance of the direct effect.

5.2.2 Effect of Changing Consumption Patterns on Variation of Policy Impacts

The standard deviation of the terms in Equation (12) across all households (i.e., both urban and rural households in all provinces) are displayed in **Table 6** and help identify the channels which drive the heterogeneous burden of climate policy. For both 2015 and 2030, the income channel has the highest standard deviation, followed by the first-order consumption channel. The variation introduced through the second order consumption channel is significantly smaller, and will thus be ignored in the following. All standard deviations are increasing in time, driven by increasing policy stringency.

Both the consumption and income channels exhibit lower variability under calibrated preferences, although the difference is more pronounced for the consumption channel. On the income side, differences between the proportional and calibrated cases are caused by the indirect effect only, a result of the lower policy stringency (which affects welfare mainly through the lower carbon price and thus moderates differences between households, as well as other general equilibrium effects).

The fact that changing consumption patterns affect the variation of impacts on the consumption side more than on the income side suggests that the direct effect plays an important role in moderating the variation of consumption side impacts (beyond the indirect effect, which affects both). To further single out this direct effect of changing consumption patterns on the consumption side, we compute the variability of the first-order consumption impacts in a hypothetical economy in which relative goods prices are identical in the calibrated and proportional cases and fixed at the 2030 level, thus abstracting from differences in policy stringency across preference assumptions and time. This is expressed by the standard deviation, across both urban and rural households in each province, of the following measure:

$$\sum_j \frac{\Delta p_j^P}{p_j^P}\bigg|_{2030} \theta_j^{P/C}\bigg|_t , \qquad (13)$$

where $\theta_j^{P/C}$ is the baseline expenditure shares for good j in the proportional (P) and calibrated (C) cases, respectively, and $\frac{\Delta p_j^P}{p_j^P}\big|_{2030}$ is the proportional change in the price of good j in 2030, for the proportional case. **Table 7** displays these standard deviations.

For fixed policy-driven price changes, the variation in direct consumption impacts of climate policy in the proportional case increases in time. This result reflects the finding from Section 4.1 that, in the proportional case, the variation in household expenditure shares increases slightly, due to relative price changes in the baseline.

The picture in the calibrated case is very different: the direct consumption impacts of policy converge rapidly. This implies that income-driven changes in household consumption patterns are significantly stronger than the offsetting effect of changes in relative prices. Overall, differences in the temporal evolution of consumption patterns cause the standard deviation to be reduced by more than half relative to the proportional case—from 3.1% to

Table 6. % consumption loss ($-\Delta S/I$): standard deviations by channel

	1st order cons		2nd order cons.		Income	
Preferences:	Calib.	Prop.	Calib.	Prop.	Calib.	Prop.
2015	0.2	0.5	0.0	0.0	1.0	1.9
2030	1.1	3.1	0.1	0.6	5.2	7.8

Table 7. %consumption loss through first-order consumption effects, holding price changes fixed at 2030 proportional case values: standard deviations

Preferences:	**Proportional**			**Calibrated**		
Year:	2007	2015	2030	2007	2015	2030
	2.4	2.6	**3.1**	2.4	1.7	**1.5**

1.5%. Comparing the 1.5% standard deviation in 2030 to the 1.1% from Table 6 suggests that a large part of the difference in the variation of consumption side impacts between the calibrated and proportional cases is due to the direct effect and is thus independent of differences in changes in relative consumption good prices under policy (caused mainly by the differing policy stringency). Note that this convergence in consumption patterns to a lesser extent drives a convergence in the production patterns and thus also indirectly reduces variability in income side effects.

Policy-induced changes in relative prices predicted by the GE model are—to a first approximation—proportional to differences in embodied carbon intensity. Thus, the convergence in impacts due to the direct effect implies that differences in the embodied energy and average carbon intensity of consumption baskets across households is declining. In other words, rising income levels in China change consumption patterns in a way that leads embodied carbon emissions to converge. This implies a catch-up in relative decarbonization: low-income households decrease the energy-intensity of their consumption baskets faster than high-income households. Using estimates of the average total carbon intensity of sectors from the 2007 base year[31], we confirm that that, by 2030, the standard deviation in the average total carbon intensity of household consumption across provinces (in kg/$) decreases from 0.17 to 0.09 (urban households) and from 0.18 to 0.09 (rural households), when moving from homothetic to non-homothetic preferences.

5.2.3 De-linking of the Income and Consumption Channels

In addition to the reduction in the variation of impacts through each channel, the variation of total impacts is also determined by the correlation between the channels. Our simulations suggest that this correlation in the first year of the policy (2015) is strong, as household types that experience above-average income losses also tend to consume a higher fraction of energy goods and be strongly affected on the consumption side. By 2030, in the proportional case, the correlation between the first order consumption and income channels is still positive and statistically significant at 0.39. In the calibrated case, on the other hand, this relationship is reversed: the correlation, –0.26, is negative (and not statistically significant), further reducing the variation of total impacts compared to the proportional case.

We identify several potential explanations for this decoupling between income and consumption channels. The first is through changes in the average tradability of the household consumption baskets. Calibrated non-homothetic preferences predict increased consumption of goods that tend to be more traded across provinces, leading to a reduced correlation between the geographical patterns of consumption and production. This is consistent with the fact that, within the set of tradable goods, income elastic goods tend to have higher export shares and be less sensitive to distance, as documented in Caron *et al.* (2014).

Low income elasticity goods are more likely to be both produced and consumed in the same provinces. For instance, the correlation between relative specialization[32] in consumption and production across provinces is high for natural gas (0.70), agriculture (0.48) and coal (0.47) whereas it is only 0.16 for oil, 0.33 for electricity and 0.11 for services. This implies that the correlation between the CO_2 intensity of consumption and production across provinces decreases from 0.51 to 0.28, going from homothetic to non-homothetic preferences.

Another source of decoupling is through the policy's impact on provincial labor wages (recall that capital costs are equalized across provinces in the model). Provinces where industry is strongly affected by policy see their wages decrease, which reduces the price of locally-produced labor-intensive services. Demand for these services tends to be relatively income elastic. Thus, in some provinces which combine carbon-intensive production (and are therefore very affected through the income channel) with a large number of middle or high income households, shifting consumption patterns towards services decreases their consumption side impacts. Consider the example of Shanxi (SX), the most affected province on the income side due to its role as a major coal producer. The large impact of policy on the energy-intensive and coal-producing industries in Shanxi depresses the demand for labor, driving down the local wage rate. This in turn reduces the price of services relative to other provinces. In the calibrated case, these price changes, combined with the relatively high share of household expenditure on services, cause households in Shanxi to be less adversely impacted than the average Chinese household. In the proportional case, on the other hand, rural households are more adversely impacted than the average Chinese households, due to their relatively high expenditure shares on coal, which is heavily targeted by policy. Greater vulnerability to carbon pricing offsets the beneficial effect of cheaper services under the policy.

In summary, we identify three main effects that cause the lower variation in policy-driven welfare impacts under

31 These are computed using a standard multi-regional Leontief inversion of the base year input-output tables which tracks all the emissions embodied in the final demand for each good.

32 Defined as the provinces share in consumption (production) in total Chinese consumption (production).

calibrated non-homothetic relative to homothetic preferences: lower policy stringency, convergence in the energy intensity of household consumption, and decoupling between consumption- and income-side impacts.

5.2.4 Impacts on the Ranking of Winners and Losers from Climate Policy

Finally, we document the extent to which non-homothetic preferences affect the ranking of household types, in terms of the welfare impacts of climate policy. Beyond the standard deviation of impacts, identifying expected winners and losers is also of interest to policy makers.

On the income side, the ranking is mostly unaffected by household preferences: Spearman's coefficient of rank correlation of income side impacts between the calibrated or proportional preference cases is 0.990 (see **Figure B2** in the Appendix for the relative distribution in impacts). The indirect effect of shifting consumption patterns thus affects household types similarly, despite the lower standard deviation found above.

On the consumption side, rank correlation between proportional and calibrated preferences is instead only 0.714 for the first order consumption channel (see **Figure B3**). This indicates that rank changes under calibrated relative to proportional preferences are driven by direct effects on the consumption side. Changes in consumption patterns can thus substantially affect who will be profiting or suffering the most from carbon pricing. Differences in ranking through the consumption channel stem from differences in average income elasticity across goods, nonlinearities in the log Engel curves and differences in baseline incomes across household types.

The reduced correlation between consumption and income channels under calibrated preferences is also very clear in terms of rankings. **Figure 8**, which plots each household types rank in consumption channel impacts against its rank in income channel impacts, illustrates the fact that many of the provinces which lose the most on the income side experience larger than average improvements on the consumption side under calibrated non-homothetic relative to homothetic preferences.

6. Conclusions

This paper investigates interactions between the income-driven dynamics of consumption patterns and climate policy, integrating Engel curve estimates from an energy-specific survey within an economy-wide calibrated general equilibrium model.

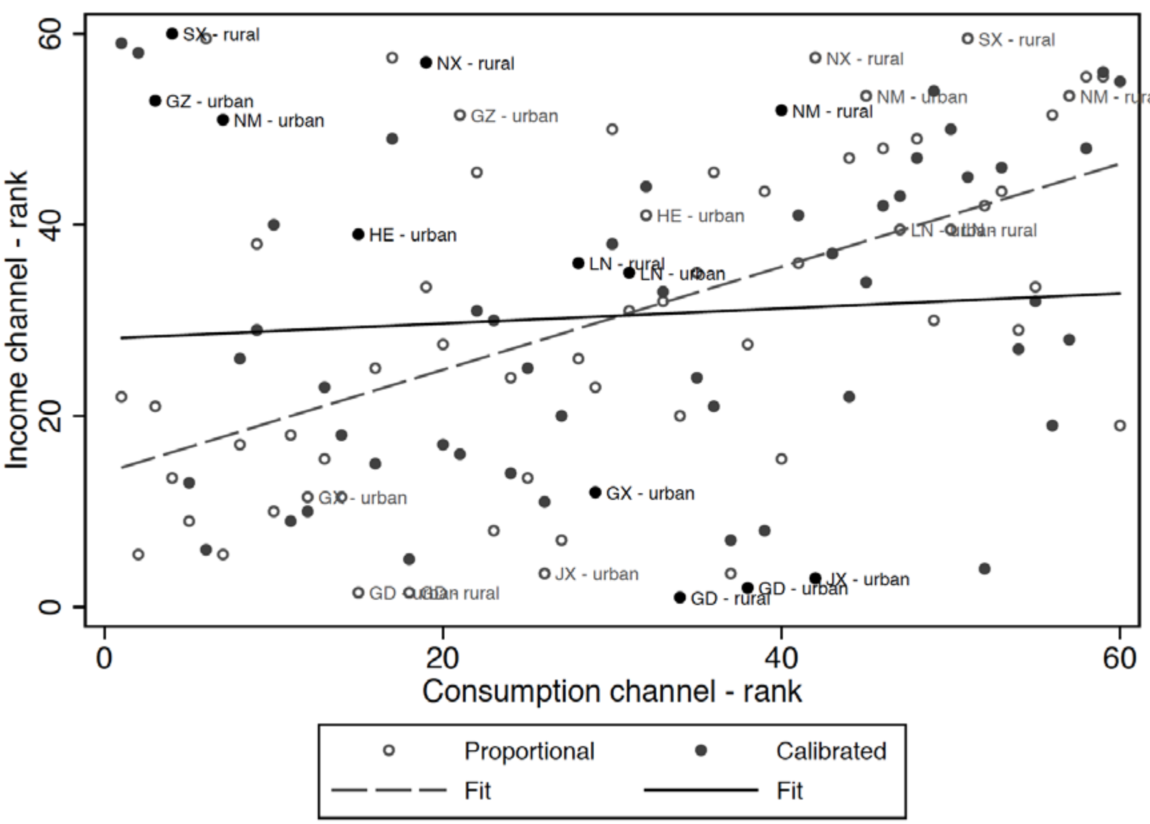


Figure 8. Rank of household welfare impacts through the income and consumption channels, for the proportional and calibrated cases. Labels correspond to provinces that see a shift of at least 15 ranks between the two cases.

In China, we find that the response of energy consumption (direct and indirect) to income growth implied by the estimated Engel curves is low. Calibrating the model to non-homothetic preferences substantially lowers energy use and CO_2 emissions projections. With calibrated preferences, direct household CO_2 emissions are 61% lower by 2030 while national emissions drop by 8%. This is good news for the climate. Absent general equilibrium feedbacks, this reduction would be even more pronounced, as a reduction in household demand lowers energy prices across the economy, prompting increased use in other sectors.

The fact that China's household consumption "grows cleaner" over time also substantially reduces the cost of achieving a given climate policy target, by delivering the mitigation that would have otherwise required a higher CO_2 price signal. While we model a specific CO_2 intensity policy consistent with China's climate pledge, lower costs with calibrated preferences are expected under any type of energy or CO_2 reduction policy. Our model also predicts that changing consumption patterns will reduce variations in energy-intensity across household consumption baskets, leading to a reduction in the variation in impacts and attenuating the regressivity of such policies.

Taken together, our results suggest that an ambitious climate policy in China may not have the dire impacts that models based on homothetic preferences would predict. Failing to capture this realism may erroneously weaken the case for ambitious policy. Viewed in this light, the extra investment in representing micro-level evolution of household consumption seems very worthwhile. While the implications of our study hold valuable lessons for other fast-growing developing countries, our findings are quantitatively and perhaps even qualitatively specific to China. While income growth may decrease the energy intensity of consumption in many countries, China's case may be extreme. Widespread access to energy, even for the poorest households, is such that the estimated energy intensity of consumption decreases with income even for the poorest households. This is likely not to be the case in many lower-income countries, where we might expect the opposite: energy use and CO_2 emissions would increase relative to projections based on homothetic preferences for poor households. Overall energy intensity and associated policy costs might be predicted to increase, at least in the short term. In some countries, the energy-intensity of consumption by the poorest households may also still further diverge from that of rich households. Distributional impacts of climate policy would thus also be predicted to further diverge.

Our approach for calibrating household preferences to estimated Engel curves for a wide range of goods within a broader general equilibrium framework could be replicated or approximated for other countries, as long as reliable Engel curve estimates from micro-data are available. Numerous countries exhibit disparities in income which are comparable to those observed in China (Xie & Zhou, 2014) and sufficiently large to perform in-sample projections of household consumption patterns such as ours. Doing so requires recognition of the methodology's limitations. Our results rely on cross-sectional data that exploit the large exiting variation in incomes and consumption patterns, but do not allow testing of the assumptions that household preferences are indeed identical across households and constant in time. Our approach also does not allow making out-of-sample predictions regarding the behavior of the richest households. While we have avoided the issue by limiting our projections to the short and medium terms, long-term projections would require additional assumptions or the use of out-of-country data. Also, we have not translated the uncertainty inherent to our empirical estimates within the simulation exercise. These issues offer interesting avenues for future research.

While conclusions may differ across countries and the impact of consumption shifts is ultimately an empirical question, our exercise does point to the importance of taking such shifts into account and suggests more generally that projection or policy-analysis models—which widely rely on unitary income elasticities—may be systematically misrepresenting the evolution of energy demand and emissions as household income rises in developing countries, yielding misleading policy prescriptions. Our findings also highlight the value of accounting for consumption shifts in a general equilibrium framework that enables the comparison of consumption *and* income side effects as well as their interactions. While our application is focused on pricing energy and emissions, our insights are relevant for assessing the impact of any taxation scheme focused on specific sectors and more generally public policies which target or interact, directly or indirectly, with patterns of household consumption.

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7. References

Abrell, J., & S. Rausch (2016). Cross-country electricity trade, renewable energy and European transmission infrastructure policy. *Journal of Environmental Economics and Management*, 79, 87–113.

Aguiar, A., B. Narayanan, & R. McDougall (2016). An overview of the GTAP 9 data base. *Journal of Global Economic Analysis*, 1, 181–208.

Aldy, J.E., W.A. Pizer, & K. Akimoto (2015). Comparing emissions mitigation efforts across countries. Discussion Paper 15–32, Resources for the Future.

Auffhammer, M., & R.T. Carson (2008). Forecasting the path of China's CO_2 emissions using province-level information. *Journal of Environmental Economics and Management*, 55, 229–247.

Auffhammer, M., & C.D. Wolfram (2014). Powering up China: Income distribution and residential electricity consumption. *American Economic Review: Papers & Proceedings*, 104, 575–580.

Bosetti, V., E. Massetti, & M. Tavoni (2004). The WITCH model. Structure, baseline, solutions. Working paper, available at: http://www.feem.it/userfiles/attach/Publication/NDL2007/NDL2007-010.pdf.

Branch, E.R. (1993). Short run income elasticity of demand for residential electricity using consumer expenditure survey data. *The Energy Journal*, 14, 111–121.

Cao, J., R. Garbaccio, & M.S. Ho (2009). China's 11th Five-Year Plan and the Environment: Reducing SO_2 Emissions. *Review of Environmental Economics and Policy*, 3, 231–250.

Cao, J., & M.S. Ho (2010). Changes in China's energy intensity: Origins and implications for long-term carbon emissions and climate policies. Report, available at: http://www.eepsea.org/pub/rr/2010-RR12-Jing%20Cao%20and%20Mun%20S%20HO.pdf.

Capros, P., D.V. Regemorter, L. Paroussos, & P. Karkatsoulis (2013). GEM-E3 model documentation. European Commission JRC Technical Report, available at: https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/gem-e3-model-documentation.

Carliner, G. (1973). Income elasticity of housing demand. *The Review of Economics and Statistics*, 55, 528–532. J. Caron, & T. Fally (2016). Per capita income, consumption patterns and CO_2 emissions. Working paper.

Caron, J., T. Fally, & J. Markusen (2014). International trade puzzles: A solution linking production and preferences. *The Quarterly Journal of Economics*, 129, 1501–1552.

Caron, J., & S. Rausch (2013). A global general equilibrium model with US state-level detail for trade and environmental policy analysis–technical notes. Number 13, MIT Joint Program Technical Note.

Caron, J., S. Rausch, & N. Winchester (2015). Leakage from sub-national climate policy: The case of California's cap-and-trade program. *Energy Journal*, 36, 167–190.

Chen, Y.-H.H., S. Paltsev, J. Reilly, J. Morris, & M. Babiker (2015). The MIT EPPA6 model: Economic growth, energy use, and food consumption. Report, available at: http://globalchange.mit.edu/files/document/MITJPSPGCRpt278.pdf.

Chern, W.S., K. Ishibashi, & K. Taniguchi (2003). Analysis of the food consumption of Japanese households. FAO Economic and Social Development Paper No. 152, available at: ftp://ftp.fao.org/docrep/fao/005/y4475E/y4475E00.pdf.

Crompton, P., & Y. Wu (2005). Energy consumption in China: past trends and future directions. *Energy Economics*, 27, 195–208.

Dai, H., T. Masui, Y. Matsuoka, & S. Fujimori (2011). Assessment of China's climate commitment and non-fossil energy plan towards 2020 using hybrid AIM/CGE model. *Energy Policy*, 39, 2875–2887.

Davis, L.W., & P.J. Gertler (2015). Contribution of air conditioning adoption to future energy use under global warming. *Proceedings of the National Academy of Sciences*, 112, 5962–5967.

Dirkse, S.P., & M.C. Ferris (1995). The PATH solver: a non-monotone stabilisation scheme for mixed complementarity problems. *Optim. Methods. Softw.*, 5, 123–156.

EIA (Energy Information Administration, U.S. D. o. E. (2017). Residential Energy Consumption Survey (RECS) - Energy Information Administration.

Engel, E. (1895). Die Lebenskosten belgischer Arbeiter-Familien frueher und jetzt. *Bulletin de l'Institut International de Statistique*, 9, 1–124.

Filippini, M., & S. Pachauri (2004). Elasticities of electricity demand in urban Indian households. *Energy Policy*, 32, 429–436.

Fullerton, D. (2011). Six distributional effects of environmental policy. *Risk Analysis*, 31, 923–929.

Fullerton, D., & G. Heutel (2007). The general equilibrium incidence of environmental taxes. *Journal of Public Economics*, 91, 571–591.

Fullerton, D., & G.E. Metcalf (2002). Tax incidence. Chapter 26, Handbook of Public Economics, Volume 4. Elsevier Science B.V.

Fullerton, D., & H. Monti (2013). Can pollution tax rebates protect low-wage earners? *Journal of Environmental Economics and Management*, 66, 539–553.

Gertler, P.J., O. Shelef, C.D. Wolfram, & A. Fuchs (2016). The demand for energy-using assets among the worlds rising middle classes. *American Economic Review*, 106, 1366–1401.

Goettle, R., M.S. Ho, D.W. Jorgenson, D.T. Slesnick, & P.J. Wilcoxen (2009). Anaylzing environmental policies with IGEM, an intertemporal general equilibrium model of U.S. growth and the environment, part 2. Available at: http://www.igem.insightworks.com/docs/247/part2chap1.pdf.

Golley, J., & X. Meng (2012). Income inequality and carbon dioxide emissions: The case of Chinese urban households. *Energy Economics*, 34, 1864 – 1872.

Goulder, L.H., & L.H. Summers (1989). Tax policy, asset prices, and growth. A general equilibrium analyis. *Journal of Public Economics*, 38, 265–296.

Hanoch, G. (1975). Production and demand models with direct and indirect implicit additivity. *Econometrica*, 43, 395–419.

Haque, M.H. (2005). Income elasticity and economic development: Methods and applications. Springer, The Netherlands.

Hertel, T. (Ed.) (1997). *Global Trade Analysis: Modeline and Applications*. Cambridge University Press.

Houthakker, H.S. (1957). An international comparison of household expenditure patterns, commemorating the centenary of Engel's law. *Econometrica*, 25, 532–551.

Jacoby, H.D., J.M. Reilly, J.R. McFarland, & S. Paltsev (2006). Technology and technical change in the MIT EPPA model. *Energy Economics*, 28, 610–631.

Leser, C.E.V. (1963). Forms of Engel functions. *Econometrica*, 31, 694–703.

Lewbel, A., & K. Pendakur (2009). Tricks with hicks: The EASI demand system. *American Economic Review*, 99, 827–863.

Li, L., Z. Song, & C. Ma (2015). Engel curves and price elasticity in urban Chinese households. *Economic Modelling*, 44, 236–242.

Liang, H., J. Cao, & M.S. Ho (2014). Household energy demand in urban China: Accounting for regional prices and rapid income change. Working Paper, available at: http://people.hmdc.harvard.edu/mho/HH%20energy%20demand%20China.2014.pdf.

Luo, X., J. Caron, D. Zhang, X. Zhang, & V. Karplus (2016). Interprovincial migration and the stringency of energy policy in China. *Energy Economics*, 58, 164–173.

Manne, A.S., & R.G. Richels (2004). MERGE: An integrated assessment model for global climate change. Technical note, available at: http://web.stanford.edu/group/MERGE/GERAD1.pdf.

Mathiesen, L. (1985). Computation of economic equilibria by a sequence of linear complementarity problems. *Math. Program. Study*, 23, 144172.

Matsuyama, K. (2016). Generalized engel's law: In search for a new theoretical framework.

van der Mensbrugghe, D. (2010). The environmental impact and sustainability applied general equilibrium (ENVISAGE) model. Working paper, available at: http://siteresources.worldbank.org/INTPROSPECTS/Resources/334934-1314986341738/Env71Jan10b.pdf.

Metcalf, G.E., S. Paltsev, J. Reilly, H. Jacoby, & J.F. Holak (2008). Analysis of U.S. greenhouse gas tax proposals. NBER Working Paper w13980.

Ming, L., & C. Zhao (2006). Urbanization, urban-biased policies, and urban-rural inequality in China, 1987-2001. *Chinese Economy*, 39, 42–63.

Munksgaard, J., K.A. Pedersen, & M. Wien (2000). Impact of household consumption on CO_2 emissions. *Energy Economics*, 22, 423–440.

Narayanan, B., A. Aguiar, & R. McDougall (Eds.) (2012). *Global Trade, Assistance, and Production: The GTAP 8 Data Base*. Center for Global Trade Analysis, Purdue University.

National Bureau of Statistics of the People's Republic of China (NBS) (2008). China energy statistical yearbook 2008.

National Bureau of Statistics of the People's Republic of China (NBS) (2011). China regional input-output tables 2007.

National Bureau of Statistics of the People's Republic of China (NBS) (2012). China statistical database. (http://www.stats.gov.cn/english/Statisticaldata).

NDRC (2015). National development and reform commission – enhanced actions on climate change: China's intended nationally determined contributions.

Nordhaus, W., & P. Sztorc (2013). DICE 2013R: Introduction and user's manual. Working Paper, available at: http://aida.wss.yale.edu/nordhaus/homepage/documents/DICE Manual 103113r2.pdf.

Paltsev, S., J. Reilly, H.D. Jacoby, R. Eckaus, J. McFarland, M. Sarofim, M. Asadoorian, & M. Babiker (2005). The mit emissions prediction and policy analysis (EPPA) model: Version 4. Volume 125, MIT Joint Program Report.

Rausch, S., & V.J. Karplus (2014). Market versus regulation: The efficiency and distributional impacts of U.S. climate policy proposals. *The Energy Journal*, 35, 199–227.

Rausch, S., G. Metcalf, & J. Reilly (2011). Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics*, 33, 20–33.

Rausch, S., G.E. Metcalf, J.M. Reilly, & S. Paltsev (2010a). Distributional implications of alternative U.S. greenhouse gas control measures. *The B.E. Journal of Economic Analysis* & *Policy*, 10. Symposium.

Rausch, S., G.E. Metcalf, J.M. Reilly, & S. Paltsev (2010b). *U.S. Energy Tax Policy*. Cambridge University Press, MA. Chapter: Distributional impacts of a U.S. greenhouse gas policy: a general equilibrium analysis of carbon pricing.

Rausch, S., & G.A. Schwarz (2016). Household heterogeneity, aggregation, and the distributional impacts of environmental taxes. *Journal of Public Economics*, 138, 43–57.

Reinders, A.H.M.E., K. Vringer, & K. Blok (2003). The direct and indirect energy requirement of households in the European Union. *Energy Policy*, 31, 139–153.

Rutherford, T.F. (1995). Extension of GAMS for complementarity problems arising in applied economics. *J. Econ. Dyn. Control*, 19, 1299–1724.

Rutherford, T.F. (1999). Applied general equilibrium modelling with MPSGE and GAMS subsystem: an overview of the modelling framework and syntax. *Comput. Econ.*, 14, 1–46.

Shi, M., N. Li, S. Zhou, Y. Yuan, & G. Ma (2010). Can China Realize CO_2 Mitigation Target Toward 2020? *Journal of Resources and Ecology*, 1, 145–154.

The World Bank (2015). Inflation, GDP deflator (annual %). Online resource, available at: http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG (accessed Mar 4, 2015).

UFCCC (2015). Sumbitted intended nationally determined contributions. United Nations (2011). World population prospects: The 2010 revision.

Wang, K., C. Wang, & J. Chen (2009). Analysis of the economic impact of different Chinese climate policy options based on a CGE model incorporating endogenous technological change. *Energy Policy*, 37, 2930–2940.

Webster, M., S. Paltsev, & J. Reilly (2008). Autonomous efficiency improvement or income elasticity of demand: Does it matter. *Energy Economics*, 30, 2785–2798.

Wei, Y.-M., L.-C. Liu, Y. Fan, & G. Wu (2007). The impact of lifestyle on energy use and {CO_2} emission: An empirical analysis of China's residents. *Energy Policy*, 35, 247 – 257.

West, S.E., & R.C. Williams III (2004). Estimates from a consumer demand system: implications for the incidence of environmental taxes. *Journal of Environmental Economics and Management*, 47, 535–558.

Williams III, R.C., H. Gordon, D. Burtraw, & J.C. Carbone (2015). The initial incidence of a carbon tax across income groups. *National Tax Journal*, 68, 195–214.

Wolfram, C., O. Shelef, & P. Gertler (2012). How will energy demand develop in the developing world? *Journal of Economic Perspectives*, 26, 119–138.

Working, H. (1943). Statistical laws of family expenditure. *Journal of the American Statistical Association*, 38, 43–56.

Xie, Y., & X. Zhou (2014). Income inequality in today's China. *Proceedings of the National Academy of Sciences of the United States of America*, 111, 6928–6933.

Zhang, D., S. Rausch, V. Karplus, & X. Zhang (2013). Quantifying regional economic impacts of CO_2 intensity targets in China. *Energy Economics*, 40, 687–701.

Zhang, X., V.J. Karplus, T. Qi, D. Zhang, & J. He (2016a). Carbon emissions in China: How far can new efforts bend the curve? *Energy Economics*, 54, 388–395.

Zhang, X., V.J. Karplus, T. Qi, D. Zhang, & J. He (2016b). Carbon emissions in China: How far can new efforts bend the curve? *Energy Economics*, 54, 388–395.

Zhang, Z. (2000). Can China afford to commit itself an emissions cap? An economic and political analysis. *Energy Economics*, 22, 587–614.

Zheng, X., C. Wei, P. Qin, J. Guo, Y. Yu, F. Song, & Z. Chen (2014). Characteristics of residential energy consumption in China: Findings from a households survey. *Energy Policy*, 75.

Zhou, Z., W. Tian, J. Wang, H. Liu, & L. Cao (2012). Food consumption trends in China. Report submitted to the Australian Government Department of Agriculture, Fisheries and Forestry.

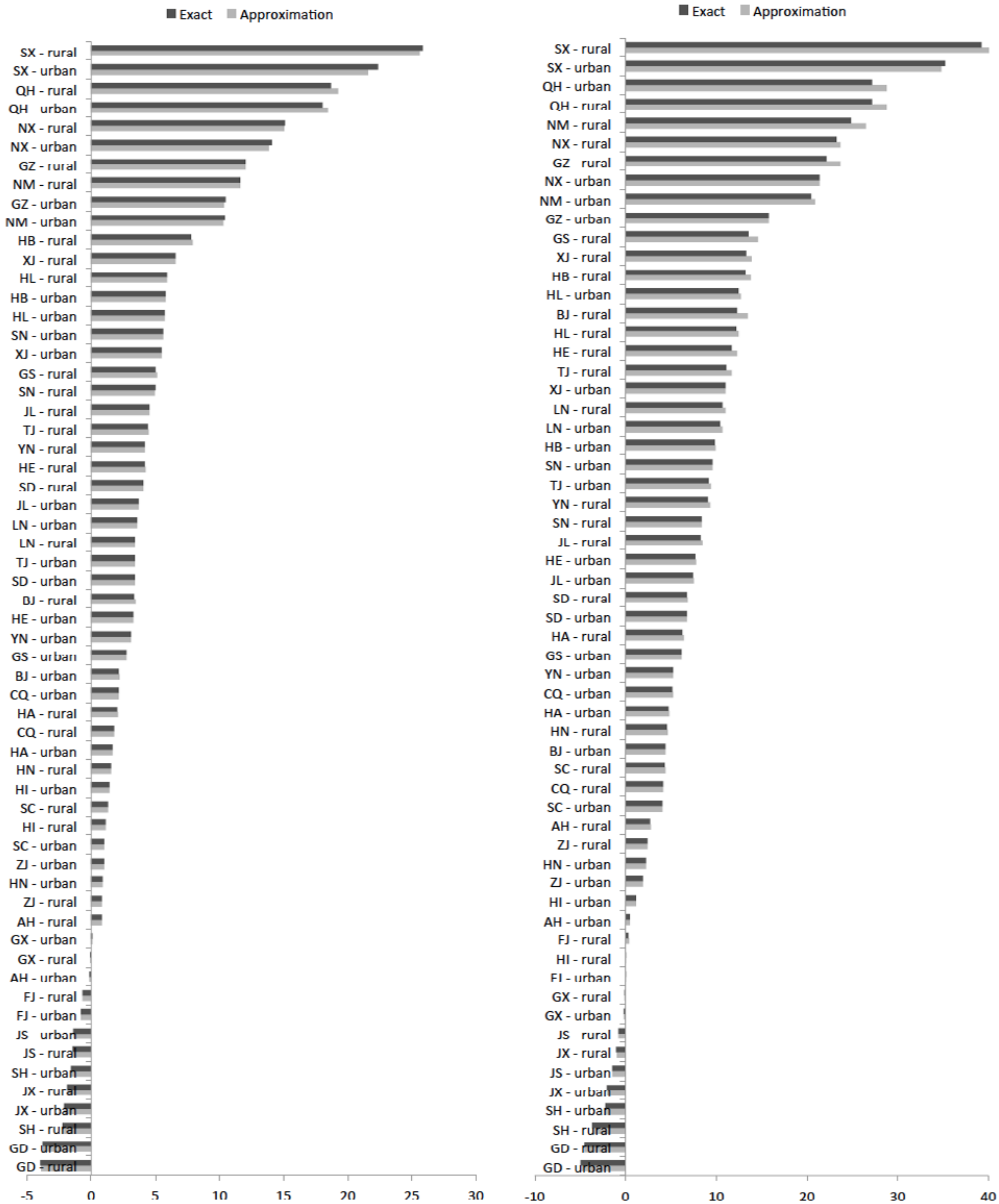
Appendix A. Issues specific to our model and data

Our model's benchmark year is 2007, but the CRECS survey as well as the NBS data we use to estimate the income curves are from 2012. In order to use the estimated Engel curves consistently in the model, we therefore convert 2007 to 2012 prices and then look up the consumption at various income levels denominated in 2012 prices. The implicit GDP deflator is used to determine the rate of inflation (The World Bank, 2015). Our general method to calibrate preferences to Engel curves is limited to cases where the projected consumption of a good remains above the benchmark consumption level (i.e., $y_{jupt} \geq x_{jupt_0}$).[33]

This holds for a given good j if its income elasticity of consumption is always positive. This is also the case if the income elasticity is initially positive, but later becomes negative as income grows—as long as the implied level of consumption never goes below the level in the benchmark year. For our model and data, however, consumption of COL and GAS for some provinces and households is decreasing to the point where the consumption levels drop below 2007 levels by 2030. For these goods, we thus resort to an alternative implementation of changing consumption patterns. We do this by scaling benchmark consumption shares to target projected consumption at benchmark prices and projected real income. For all other goods, we employ the calibration described in Section 3.3.3. Regarding the convergence of the iterative routine involved in the calibration of preferences, we find that the difference in real income between the second and the first iteration of the calibration process varies widely by province and household type, with a magnitude relative to the 2030 real income as large as 10.5%. This difference drops sharply, and the fourth iteration delivers differences that are significantly lower than 0.1%, at which point we terminate the iteration.

33 If this condition does not hold, the calibration would then imply $c^{\star}_{jupt} > x_{jupt_0}$, and as a consequence $\tilde{\theta} < 0$, which cannot hold.

Appendix B. Additional graphs



(a) Calibrated (b) Proportional

Figure B1. %consumption loss in 2030: comparison between exact measure (equivalent variation) and approximation (consumer surplus), for the calibrated and the proportional cases.

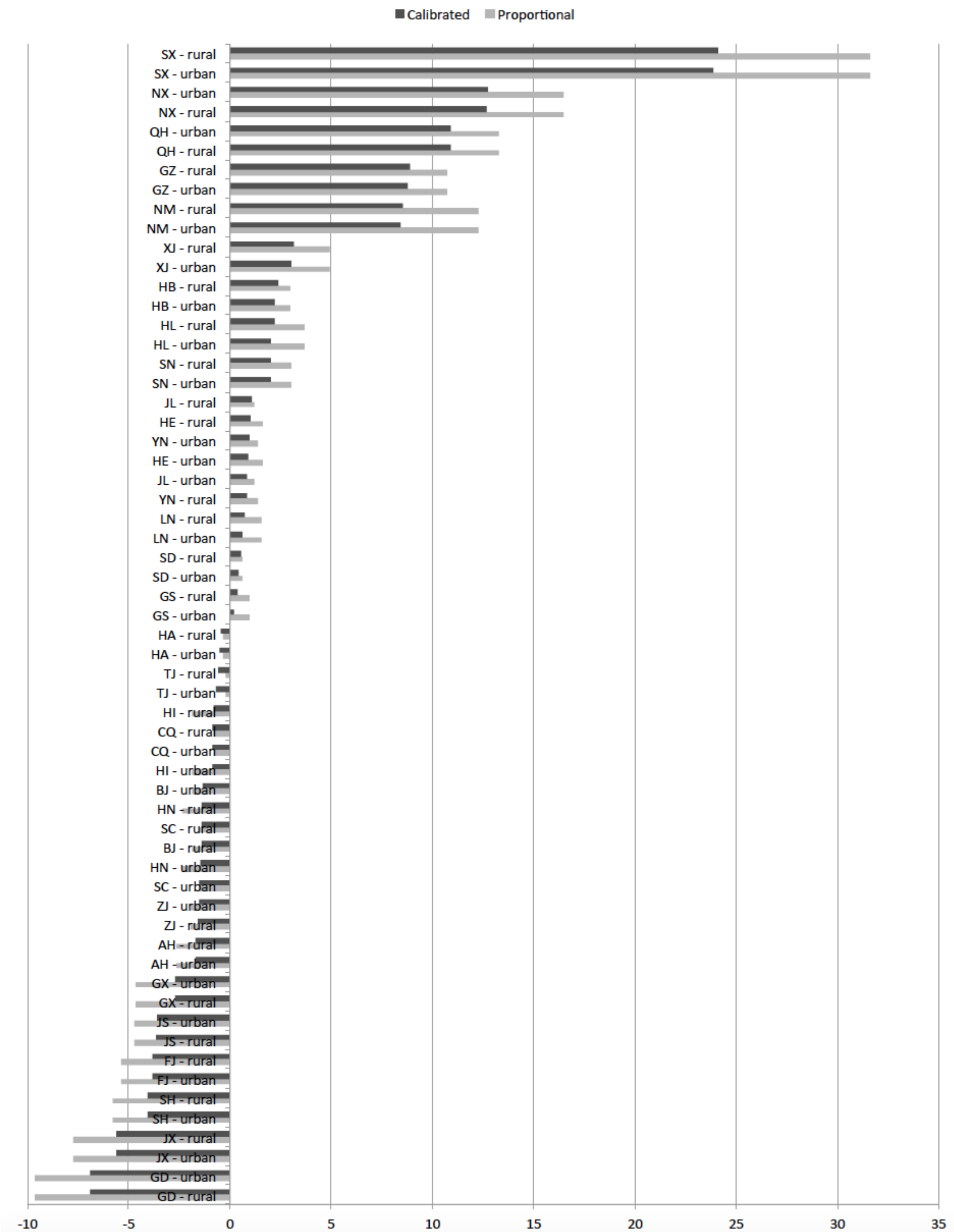


Figure B2. % welfare loss in 2030 through the income channel (relative to the population-weighted average impact through this channel).

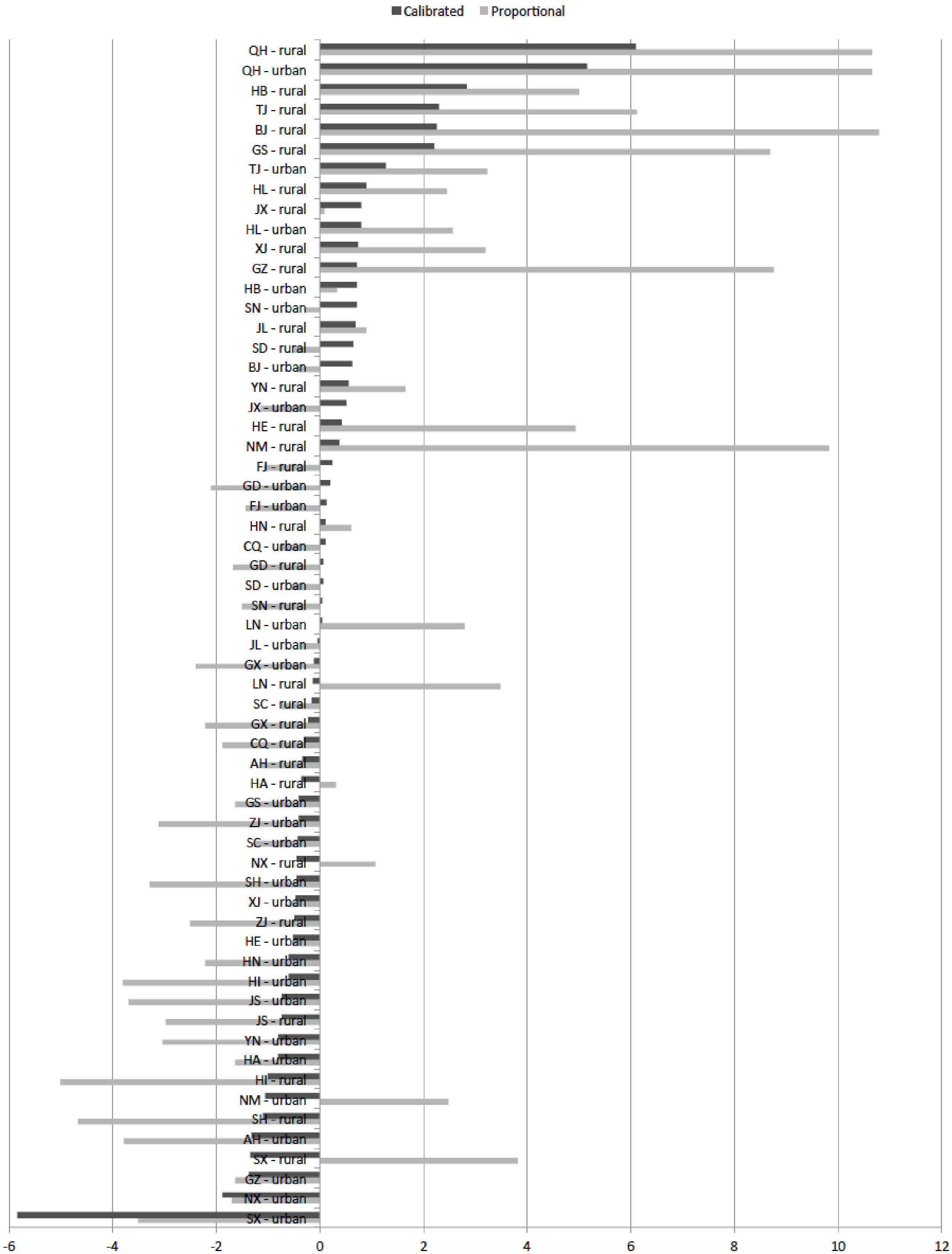


Figure B3. % welfare loss in 2030 through the 1st order consumption channel (relative to the population-weighted average impact through this channel).

Appendix C. Equilibrium conditions for the general equilibrium model

We formulate our model as a non-linear complementarity problem (Rutherford, 1995).[34] The economic equilibrium is characterized by a system of non-linear inequalities, comprizing zero profit and market clearing conditions.[35] Zero-profit conditions are complementary to quantity variables, and market clearing conditions are complementary to price variables. Model variables and parameters are defined in **Tables C1 to C4**. We start by defining the unit cost functions c, which enter the zero profit conditions. Household welfare is assumed to consist of a Cobb-Douglas function of household consumption, leisure, and savings. The associated cost function therefore assumes the following form:

$$c^{W}_{\bar{h}r} := P_{\bar{h}s}^{\tilde{\theta}^{W,CON}_{\bar{h}r}} \; P_{INV,r}^{\theta^{W,SAV}_{\bar{h}r}} \; PL_r^{1-\tilde{\theta}^{W,CON}_{\bar{h}r}-\theta^{W,SAV}_{\bar{h}r}}$$

The unit cost function for utility from consumption is defined as (**Figure C1**):[36]

$$c^{C}_{\bar{h}r} := \left[\tilde{\theta}^{TRN}_{\bar{h}r}\left(\frac{PAT_{TRNr}}{\overline{pat}_{TRNr}}\right)^{1-\sigma_{ctop}} + \left(1-\tilde{\theta}^{TRN}_{\bar{h}r}\right)\left(c^{NTRN}_{\bar{h}r}\right)^{1-\sigma_{ctop}}\right]^{\frac{1}{1-\sigma_{ctop}}}$$

where

$$c^{NTRN}_{\bar{h}r} := \left[\tilde{\theta}^{CON}_{\bar{h}r}\left(c^{CENE}_{\bar{h}r}\right)^{1-\sigma_{cntrn}} + \left(1-\tilde{\theta}^{CON}_{\bar{h}r}\right)\left(c^{CCON}_{\bar{h}r}\right)^{1-\sigma_{cntrn}}\right]^{\frac{1}{1-\sigma_{cntrn}}}$$

$$c^{CENE}_{\bar{h}r} := \left[\sum_{j\in ENE}\tilde{\theta}^{CENE}_{j\bar{h}r}\left(\frac{PAT_{jr}}{\overline{pat}_{jr}}\right)^{1-\sigma_{cene}}\right]^{\frac{1}{1-\sigma_{cene}}}$$

$$c^{CCON}_{\bar{h}r} := \left[\sum_{j\in NENE\setminus\{TRN\}}\tilde{\theta}^{CCON}_{j\bar{h}r}\left(\frac{PAT_{jr}}{\overline{pat}_{jr}}\right)^{1-\sigma_{ccon}}\right]^{\frac{1}{1-\sigma_{ccon}}},$$

where PAT jr denote carbon cost inclusive Armington prices.[37] For government and investment consumption, unit cost functions c^G_r and c^I_r are defined similarly as for private consumption (**Figure C2**):

$$c^{G/I}_{r} := \left[\theta^{G/ICON}_{r}\left(c^{G/ICENE}_{r}\right)^{1-\sigma_{gitop}} + \left(1-\theta^{G/ICON}_{r}\right)\left(c^{G/ICCON}_{r}\right)^{1-\sigma_{gitop}}\right]^{\frac{1}{1-\sigma_{gitop}}}$$

---

34 As this part of the model is based on Zhang *et al.* (2013), the model description will follow the previous exposition closely. It is also similar to other descriptions of models of this type, such as Caron & Rausch (2013) and Abrell & Rausch (2016).

35 In general, a non-linear complementarity problem assumes the following form (Rutherford, 1995): given a function $F: \mathbb{R}^n \longrightarrow \mathbb{R}^n$, find $z \in \mathbb{R}^n$ such that $F(z) \geq 0$, $z \geq 0$, and $z^T F(z) = 0$, or, in compact notation, $F(z) \geq 0 \perp z \geq 0$, indicating complementarity between equilibrium condition and variable.

36 Prices denoted with an upper bar stand for tax-inclusive benchmark values. Note that, for simplicity, we abstract in the notation from the fact that such prices are differentiated across agents, due to differentiated tax rates. θ generally refers to share parameters.

37 The carbon cost is to be added to PA in proportion to the good's carbon intensity.

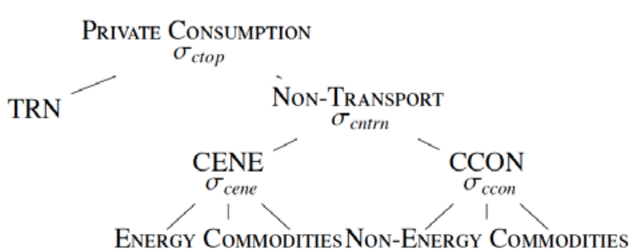


Figure C1. Structure of Private Consumption

Unit cost functions for production activities $j \in$ {EIS, MAN, WTR, CON, TRN, SER, AGR, OMN} are given as (**Figures C3 and C4**):

$$c_{jr} := \left[\sum_{j' \in NENE} \theta^{TOP}_{j'jr} \left(\frac{PAT_{j'r}}{\overline{\overline{pat}}_{j'r}} \right)^{1-\sigma_{ytop}} + \theta^{RES}_{jr} \left(\frac{PS_{jr}(1+ts_{jr})}{\overline{\overline{ps}}_{jr}} \right)^{1-\sigma_{ytop}} + \left(1 - \theta^{RES}_{jr} - \sum_{j' \in NENE} \theta^{TOP}_{j'jr} \right) (c^{VAE}_{jr})^{1-\sigma_{ytop}} \right]^{\frac{1}{1-\sigma_{ytop}}}$$

where

$$c^{VAE}_{jr} := \left[\theta^{VAE}_{jr} (c^{VA}_{jr})^{1-\sigma_{vae}} + \left(1 - \theta^{VAE}_{jr}\right) (c^{ENE}_{jr})^{1-\sigma_{vae}} \right]^{\frac{1}{1-\sigma_{vae}}}$$

$$c^{VA}_{jr} := \left[\theta^{VA}_{jr} \left(\frac{(1+tl_{jr})PL_r}{\overline{\overline{pl}}_{jr}} \right)^{1-\sigma_{va}} + \left(1 - \theta^{VA}_{jr}\right) \left(\frac{(1+tk_{jr})PK_r}{\overline{\overline{pk}}_{jr}} \right)^{1-\sigma_{va}} \right]^{\frac{1}{1-\sigma_{va}}}$$

$$c^{ENE}_{jr} := \left[\theta^{ENE}_{jr} \left(\frac{PAT_{ELE,r}}{\overline{\overline{pat}}_{ELE,r}} \right)^{1-\sigma_{ene}} + \left(1 - \theta^{ENE}_{jr}\right) (c^{FOF}_{jr})^{1-\sigma_{ene}} \right]^{\frac{1}{1-\sigma_{ene}}}$$

$$c^{FOF}_{jr} := \left[\sum_{j' \in FOF} \theta^{FOF}_{j'jr} \left(\frac{PAT_{j'r}}{\overline{\overline{pat}}_{j'r}} \right)^{1-\sigma_{fof}} \right]^{\frac{1}{1-\sigma_{fof}}} .$$

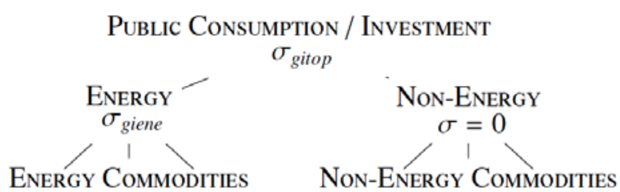


Figure C2. Structure of Government Consumption and Investment

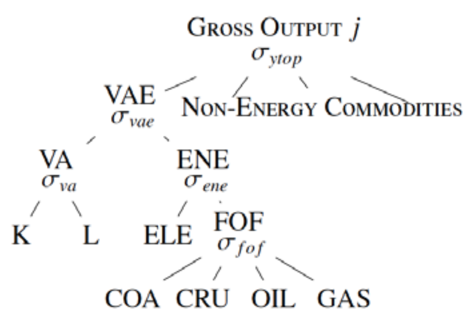


Figure C3. Structure of Production for $j \in$ {EIS, MAN, WTR, CON, TRN, SER}

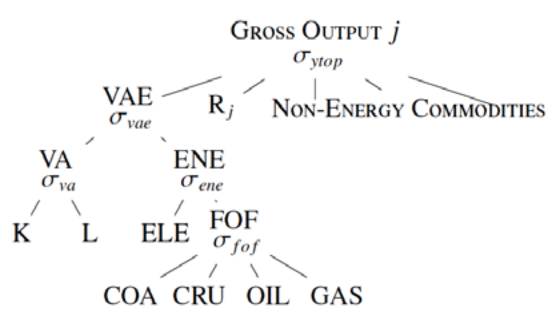


Figure C4. Structure of Production for $j \in$ {AGR, OMN}

Note that for Chinese provinces p, there is a single capital rental rate, since capital markets within China are assumed to be integrated. Thus $PK_p \equiv PK^{CHN}, \forall p \in$ CHN. Unit cost functions for production activity $j \in$ {OIL} are analogous to those for $i \in$ {EIS, MAN, ... } from above, with the top level elasticity set to zero (**Figure C5**): The unit cost function for production activity $j \in$ {ELE} is given as (**Figure C6**):

$$c_{jr} := min\left\{c_{NUC,r},\ c_{HYD,r},\ c_{WYD,r},\ c_r^{CGO}\right\}$$

where

$$c_{nhw,r} := \left[\theta_{nhw,r}^{TOP}\left(\frac{(1+tsn_{nhw,r})PS_{nhw,r}}{\overline{\overline{psnhw_{nhw,r}}}}\right)^{1-\sigma_{nhwtpo}} + \left(1-\theta_{nhw,r}^{TOP}\right)\left(c_{nhw,r}^{VAM}\right)^{1-\sigma_{nhwtop}}\right]^{\frac{1}{1-\sigma_{nhwtop}}}$$

$$c_{nhw,r}^{VAM} := \theta_{nhw,r}^{SER}\left(\frac{PAT_{SER,r}}{\overline{\overline{pat_{SER,r}}}}\right) + \left(1-\theta_{nhw,r}^{SER}\right)c_{nhw,r}^{VA}$$

$$c_{nhw,r}^{VA} := \left[\theta_{nhw,r}^{VA}\left(\frac{(1+tl_{nhw,r})PL_r}{\overline{\overline{pl_{nhwr}}}}\right)^{1-\sigma_{va}} + \left(1-\theta_{nhw,r}^{VA}\right)\left(\frac{(1+tk_{nhw,r})PK_r}{\overline{\overline{pk_{nhw,r}}}}\right)^{1-\sigma_{va}}\right]^{\frac{1}{1-\sigma_{va}}}$$

and

$$c_r^{CGO} := \left[\sum_{cgo\in CGO}\theta_{cgo,r}^{CGO}\left(c_{cgo,r}^{CGO}\right)^{1-\sigma_{cgo}}\right]^{\frac{1}{1-\sigma_{cgo}}}$$

$$c_{cgo,r}^{CGO} := \sum_{j\in J\setminus\{ELE\}}\theta_{j,cgo,r}\frac{PAT_{jr}}{\overline{\overline{pat_{jr}}}} + \left(1-\sum_{j\in J\setminus\{ELE\}}\theta_{j,cgo,r}\right)c_{cgo,r}^{VAE}$$

$$c_{cgo,r}^{VAE} := \left[\left(1-\theta_{cgo,r}^{VA}\right)\left(\frac{PAT_{ELE,r}}{\overline{\overline{pat_{ELE,r}}}}\right)^{1-\sigma_{vae}} + \theta_{cgo,r}^{VA}\left(c_{cgo,r}^{VA}\right)^{1-\sigma_{vae}}\right]^{\frac{1}{1-\sigma_{vae}}}$$

$$c_{cgo,r}^{VA} := \left[\theta_{cgo,r}^{L}\left(\frac{(1+tl_{cgo,r})PL_r}{\overline{\overline{pl_{cgo,r}}}}\right)^{1-\sigma_{va}} + \left(1-\theta_{cgo,r}^{L}\right)\left(\frac{(1+tk_{cgo,r})PK_r}{\overline{\overline{pk_{cgo,r}}}}\right)^{1-\sigma_{va}}\right]^{\frac{1}{1-\sigma_{vae}}}$$

Unit cost functions for production activities $j \in$ {COL, CRU, GAS} are given as (**Figure C7**):

$$c_{jr} := \left[\theta_{jr}^{MAT}\left(c_{jr}^{MAT}\right)^{1-\sigma_{ytop}} + \theta_{jr}^{RES}\left(\frac{PS_{jr}(1+ts_{jr})}{\overline{\overline{ps_{jr}}}}\right) + \left(1-\theta_{jr}^{MAT}-\theta_{jr}^{RES}\right)\left(c_{jr}^{VAE}\right)^{1-\sigma_{ytop}}\right]^{\frac{1}{1-\sigma_{ytop}}}$$

where

$$c_{jr}^{MAT} := \sum_{j'\in NENE}\theta_{j'jr}^{CMAT}\frac{PAT_{j'r}}{\overline{\overline{pat_{j'r}}}}$$

$$c_{jr}^{VAE} := \left[\theta_{jr}^{LVAE}\left(\frac{(1+tl_{jr})PL_r}{\overline{\overline{pl_{jr}}}}\right)^{1-\sigma_{kle}} + \theta_{jr}^{KVAE}\left(\frac{(1+tk_{jr})PK_r}{\overline{\overline{pk_{jr}}}}\right)^{1-\sigma_{kle}} + \sum_{j'\in ene}\theta_{j'jr}^{EVAE}\left(\frac{(1+ti_{j'r})PAT_{j'r}}{\overline{\overline{pat_{j'r}}}}\right)^{1-\sigma_{kle}}\right]^{\frac{1}{1-\sigma_{kle}}}$$

Transporting commodity j from region r to region r' requires services from the transportation sector. The import price for commodity j produced in region r and shipped to region r' therefore amounts to: $(1+te_{jr})P_{jr} + \phi_{jrr'}^{T}PT$, for routes involving international transport and $(1+te_{jr})P_{jr} + \phi_{jrr'}^{T}P_{TRN,r}$ for domestic routes, where te_{jr} is the export tax collected in region r and $\phi_{jrr'}^{T}$ is the amount of (international or domestic) transport commodity needed to

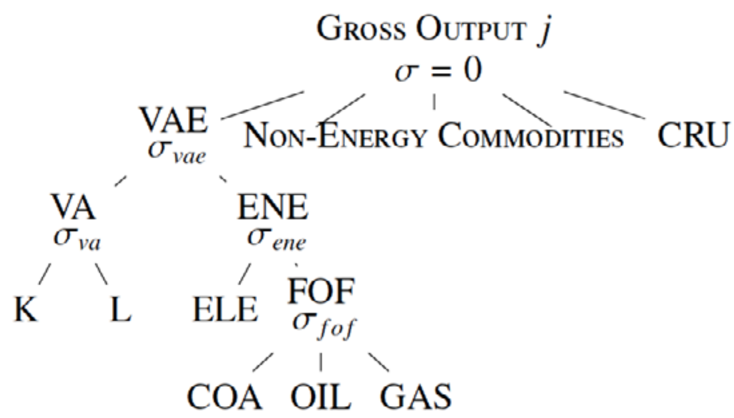


Figure C5. Structure of Production for $j \in$ {OIL}

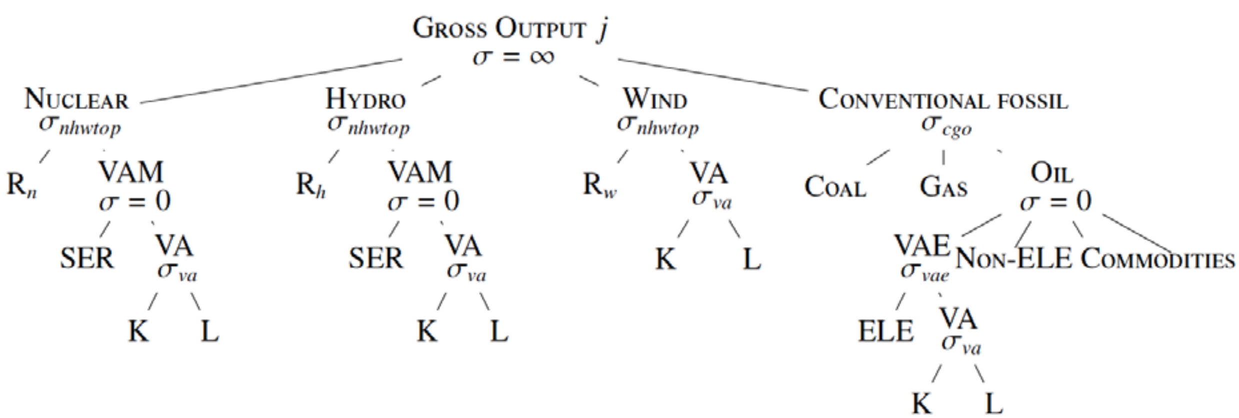


Figure C6. Structure of Production for $j \in$ {ELE}

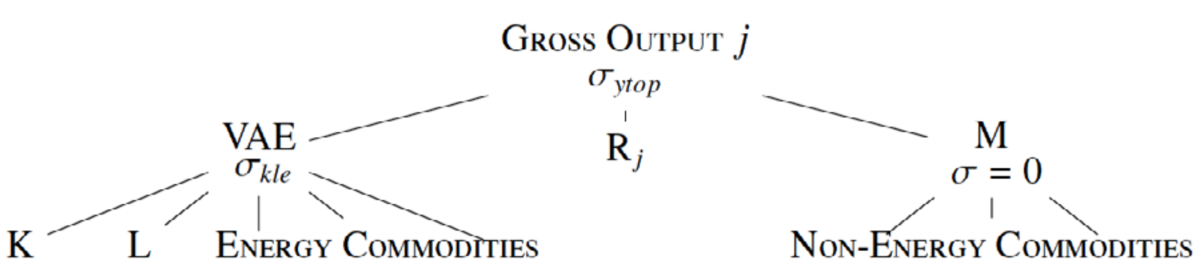


Figure C7. Structure of Production for $j \in$ {COAL, CRU, GAS} transport commodity j. For simplicity, we abstract from import subsidies. The unit cost function for the Armington commodity for region r is (**Figures C8 and C9**):

$$c_{jr}^{A} := \left[\theta_{jr}^{A}\left(c_{jr}^{D}\right)^{1-\sigma_{a,j}} + \left(1-\theta_{jp}^{A}\right)\left(c_{jp}^{M}\right)^{1-\sigma_{a,j}}\right]^{\frac{1}{1-\upsilon_{a,j}}}$$

The unit cost function for the imported composite in China province p is:

$$c_{jp}^{M} := \left[\sum_{s}\theta_{jsp}^{M}\left(\left(1+tm_{jr}^{INT}\right)\frac{\left(1+te_{js}\right)P_{js}+\phi_{jsp}^{T}PT}{\overline{pm}_{jsp}}\right)^{1-\sigma_{f,j}}\right]^{\frac{1}{1-\sigma_{f,j}}}$$

The unit cost function for the domestic composite in China province p is:

$$c_{jp}^{D} := \left[\theta_{jp}^{D}\left(\left(1+td_{jr}\right)\frac{P_{jp}}{\overline{pd}_{jp}}\right)^{1-\sigma_{c,j}} + \left(1-\theta_{jp}^{D}\right)\left(c_{jp}^{DC}\right)^{1-\sigma_{c,j}}\right]^{\frac{1}{1-\sigma_{c,j}}}$$

with

$$c_{jp}^{DC} := \left[\sum_{p'}\theta_{jp'p}^{DC}\left(\left(1+tm_{jp}^{CHN}\right)\frac{\left(1+te_{jp'}\right)P_{jp'}+\phi_{jp'p}^{T}P_{TRN,p'}}{\overline{pm}_{jp'p}}\right)^{1-\sigma_{c,j}}\right]^{\frac{1}{1-\sigma_{c,j}}}.$$

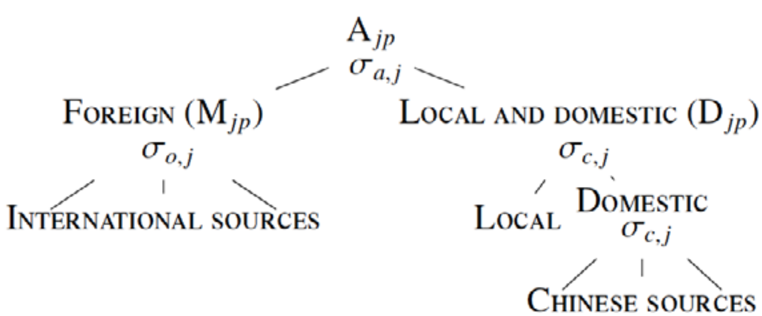


Figure C8. Aggregation of local, domestic, and foreign varieties of good j for China province p

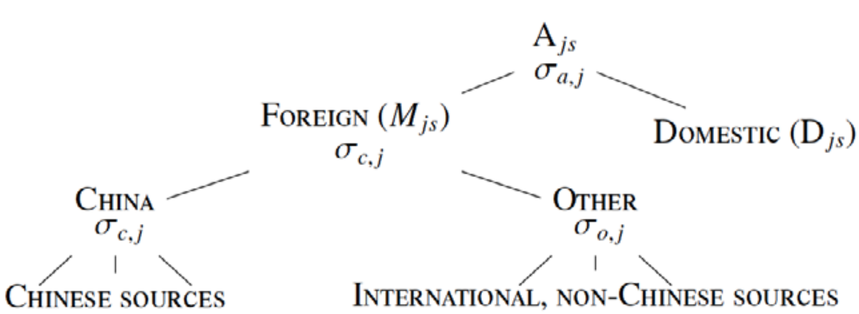


Figure C9. Aggregation of domestic and foreign varieties of good j for international region s

The unit cost function for the imported composite for international region s is

$$c_{js}^{M} := \left[\theta_{js}^{M}\left(c_{js}^{MC}\right)^{1-\sigma_{c,j}} + \left(1-\theta_{js}^{M}\right)\left(c_{js}^{MNC}\right)^{1-\sigma_{c,j}}\right]^{\frac{1}{1-\sigma_{c,j}}}$$

with

$$c_{js}^{MC} := \left[\sum_{p}\theta_{jps}^{MC}\left(\left(1+tm_{js}^{CHN}\right)\frac{\left(1+te_{jp}\right)P_{jp}+\phi_{jps}^{T}PT}{\overline{pm}_{jps}}\right)^{1-\sigma_{c,j}}\right]^{\frac{1}{1-\sigma_{c,j}}}$$

$$c_{js}^{MNC} := \left[\sum_{s'}\theta_{js's}^{MNC}\left(\left(1+tm_{js}^{INT}\right)\frac{\left(1+te_{js'}\right)P_{js'}+\phi_{js's}^{T}PT}{\overline{pm}_{js's}}\right)^{1-\sigma_{o,j}}\right]^{\frac{1}{1-\sigma_{o,j}}}.$$

The unit cost function for the domestic composite for international region s is simply

$$c_{js}^{D} := \left(1+td_{jr}\right)\frac{P_{js}}{\overline{pd}_{js}}$$

International transport services are produced with transport services from each region according to a Cobb-Douglas function:

$$c^{T} := \prod_{r} P_{TRN,r}^{\theta_r^T},$$

where θ_r^T is the cost share of region r transport commodity in the international transport services composite. The model's **zero-profit conditions** are then given by:

$$
\begin{array}{lll}
c_{\bar{h}r}^{W} \geq PW_{\bar{h}r} & \perp \quad W_{\bar{h}r} \geq 0 & \forall \bar{h}, r \\
c_{\bar{h}r}^{C} \geq P_{\bar{h}r} & \perp \quad Y_{\bar{h}r} \geq 0 & \forall \bar{h}, r \\
c_{r}^{G} \geq P_{GOV,r} & \perp \quad Y_{GOV,r} \geq 0 & \forall r \\
c_{r}^{I} \geq P_{INV,r} & \perp \quad Y_{INV,r} \geq 0 & \forall r \\
c_{jr} \geq (1-to_{jr})P_{jr} & \perp \quad Y_{jr} \geq 0 & \forall j, r \\
c_{jr}^{A} \geq PA_{jr} & \perp \quad A_{jr} \geq 0 & \forall j, r \\
c_{jr}^{D} \geq PD_{jr} & \perp \quad D_{jr} \geq 0 & \forall j, r \\
c_{jr}^{M} \geq PM_{jr} & \perp \quad M_{jr} \geq 0 & \forall j, r \\
c^{T} \geq PT & \perp \quad T \geq 0 & \forall r
\end{array}
$$

Using Shephard's lemma, **market clearing equations** become:

$$Y_{jp} \geq \sum_s \frac{\partial c^M_{js}}{\partial P_{jp}} M_{js} + \sum_{p'} \frac{\partial c^D_{jp'}}{\partial P_{jp}} D_{jp} + \frac{\partial c^T}{\partial P_{jp}} T \qquad \perp \quad P_{jp} \geq 0 \qquad \forall j, p$$

$$Y_{js} \geq \sum_p \frac{\partial c^M_{jp}}{\partial P_{js}} M_{jp} + \sum_{s' \neq s} \frac{\partial c^M_{js'}}{\partial P_{js}} M_{js'} + \frac{\partial c^D_{js}}{\partial P_{js}} D_{js} + \frac{\partial c^T}{\partial P_{js}} T \qquad \perp \quad P_{js} \geq 0 \qquad \forall j, s$$

$$Y_{INV,r} \geq \sum_{\bar{h}} \frac{\partial c^W_{\bar{h}r}}{\partial P_{INV,r}} W_{\bar{h}r} \qquad \perp \quad P_{INV,r} \geq 0 \qquad \forall r$$

$$Y_{\bar{h},r} \geq \sum_{\bar{h}} \frac{\partial c^W_{\bar{h}r}}{\partial P_{\bar{h},r}} W_{\bar{h}r} \qquad \perp \quad P_{\bar{h},r} \geq 0 \qquad \forall \bar{h}, r$$

$$D_{jr} \geq \frac{\partial c^A_{jr}}{\partial PD_{jr}} D_{jr} \qquad \perp \quad PD_{jr} \geq 0 \qquad \forall j, r$$

$$M_{jr} \geq \frac{\partial c^A_{jr}}{\partial PM_{jr}} M_{jr} \qquad \perp \quad PM_{jr} \geq 0 \qquad \forall j, r$$

$$A_{jr} \geq \sum_{j}^{\prime} \frac{\partial c_{j'r}}{\partial PA_{jr}} Y_{j'r} + \sum_{\bar{h}} \frac{\partial c^C_{\bar{h}r}}{\partial PA_{jr}} C_r + \frac{\partial c^G_r}{\partial PA_{jr}} G_r + \frac{\partial c^I_r}{\partial PA_{jr}} I_r \qquad \perp \quad PA_{jr} \geq 0 \qquad \forall j, r$$

$$\overline{L}_r \geq \sum_j \frac{\partial c_{jr}}{\partial PL_r} Y_{ir} + \sum_{\bar{h}} \frac{\partial c^W_{\bar{h}r}}{\partial PL_r} W_{\bar{h}r} \qquad \perp \quad PL_r \geq 0 \qquad \forall r$$

$$\overline{K}_s \geq \sum_j \frac{\partial c_{js}}{\partial PK_s} Y_{js} \qquad \perp \quad PK_s \geq 0 \qquad \forall s \in INT$$

$$\overline{K}_p \geq \sum_{jp} \frac{\partial c_{jp}}{\partial PK^{CHN}} Y_{jp} \qquad \perp \quad PK^{CHN} \geq 0$$

$$\sum_{\bar{h}} \overline{R}_{j\bar{h}r} \geq \frac{\partial c_{jr}}{\partial PS_{jr}} Y_{jr} \qquad \perp \quad PS_{jr} \geq 0 \qquad \forall j, r$$

$$\sum_{\bar{h}} \overline{R}_{nhw,\bar{h}r} \geq \frac{\partial c_{nhw,r}}{\partial PS_{nhw,r}} Y_{nhw,r} \qquad \perp \quad PS_{nhw,r} \geq 0 \qquad \forall nhw, r$$

$$T \geq \sum_{j'r} \frac{\partial c^A_{j'r}}{\partial PT} A_{j'r} \qquad \perp \quad PT \geq 0 \qquad \forall r$$

$$W_{\bar{h}r} \geq \frac{INC^C_{\bar{h}r}}{P_{\bar{h}r}} \qquad \perp \quad PW_{\bar{h}r} \geq 0 \qquad \forall \bar{h}, r$$

$$Y_{GOV,r} \geq \frac{INC^G_r}{P_{GOV,r}} \qquad \perp \quad P_{GOV,r} \geq 0 \qquad \forall r,$$

where $\bar{L}_r \equiv \sum_{\bar{h}} \bar{L}_{\bar{h}r}$, $\bar{K}_r \equiv \sum_{\bar{h}} \bar{K}_{\bar{h}r}$, and $\bar{L}_{\bar{h}r} \bar{K}_{\bar{h}r}$, $\bar{R}_{j\bar{h}r}$, and $\bar{R}_{nhw,\bar{h}r}$ are consumers' endowments of labor, capital, and natural resources, respectively. Household income in the model amounts to factor income net of a lump sum payment to the local government and of payment for minimum consumption. Government income is the sum of all tax revenues:

$$INC^{C}_{\bar{h}r} := PL_r \bar{L}_{\bar{h}r} + PK_r \bar{K}_{\bar{h}r} + \sum_{j} PS_{jr} \bar{R}_{j\bar{h}r} + \sum_{nhw} PS_{nhw,r} \bar{R}_{nhw,\bar{h}r} - htax_{\bar{h}r} - \sum_{j} PAT_{jr} c^{\star}_{j\bar{h}r}$$

$$\begin{aligned}
INC^{G}_{p} := & \sum_{j} Y_{jp} \left[tl_p PL_p \frac{\partial c_{jp}}{\partial PL_p} + tk_p PK_p \frac{\partial c_{jp}}{\partial PK_p} + ts_p PS_{jp} \frac{\partial c_{jp}}{\partial PS_{jp}} + \sum_{nhw} tsn_{nhw,p} PS_{nhw,p} \frac{\partial c_{jp}}{\partial PS_{nhw,p}} \right] \\
& + \sum_{j} to_{jp} P_{jp} Y_{jp} + \sum_{j} td_{jp} P_{jp} \frac{\partial c^{D}_{jp}}{\partial P_{jp}} D_{jp} \\
& + \sum_{j,p' \neq p} tm^{CHN}_{jp} \left[(1 + te_{jp'}) P_{jp'} + \phi^{T}_{jp'p} P_{TRN,p} \right] \frac{\partial c^{D}_{jp}}{\partial P_{jp'}} D_{jp} + \sum_{js} tm^{INT}_{jp} \left[(1 + te_{js}) P_{js} \phi^{T}_{jsp} PT \right] \frac{\partial c^{M}_{jp}}{\partial P_{js}} M_{jp} \\
& + \sum_{j,p' \neq p} te_{jp} P_{jp} \frac{\partial c^{D}_{jp'}}{\partial P_{jp}} D_{jp'} + \sum_{j,s} te_{jp} P_{jp} \frac{\partial c^{M}_{js}}{\partial P_{jp}} M_{js} \\
& + htax_p
\end{aligned}$$

$$\begin{aligned}
INC^{G}_{s} := & \sum_{j} Y_{js} \left[tl_s PL_r \frac{\partial c_{js}}{\partial PL_s} + tk_s PK_s \frac{\partial c_{js}}{\partial PK_s} + ts_s PS_{js} \frac{\partial c_{js}}{\partial PS_{js}} + \sum_{nhw} tsn_{nhw,s} PS_{nhw,s} \frac{\partial c_{js}}{\partial PS_{nhw,s}} \right] \\
& + \sum_{j} to_{js} P_{js} Y_{js} + \sum_{j} td_{js} P_{js} \frac{\partial c^{D}_{js}}{\partial P_{js}} D_{js} \\
& + \sum_{jp} tm^{CHN}_{js} \left[(1 + te_{jp}) P_{jp} + \phi^{T}_{jps} PT \right] \frac{\partial c^{M}_{js}}{\partial P_{jp}} D_{js} + \sum_{j,s' \neq s} tm^{INT}_{js} \left[(1 + te_{js'}) P_{js'} \phi^{T}_{js's} PT \right] \frac{\partial c^{M}_{js}}{\partial P_{j,s'}} M_{js} \\
& + \sum_{jp} te_{js} P_{js} \frac{\partial c^{M}_{jp}}{\partial P_{js}} M_{jp} + \sum_{j,s' \neq s} te_{js} P_{js} \frac{\partial c^{M}_{js'}}{\partial P_{js}} M_{js'} \\
& + htax_s \, .
\end{aligned}$$

Table C1. C-REM regions, sectors and households

Regions $r \in R$						**Sectors** $j \in J$	
AH	Anhui	**HE**	Hebei	**QH**	Qinghai	**AGR**	Agriculture, forestry, livestock
BJ	Beijing	**HI**	Hainan	**SC**	Sichuan	**COL**	Coal mining and processing
CQ	Chongqing	**HL**	Heilongjiang	**SD**	Shandong	**CON**	Construction
FJ	Fujian	**HN**	Hunan	**SH**	Shanghai	**CRU**	Crude petroleum products
GD	Guandong	**JL**	Jilin	**SN**	Shaanxi	**EIS**	Energy intensive industries
GS	Gansu	**JS**	Jiangsu	**SX**	Shanxi	**ELE**	Electricity and heat
GX	Guanxi	**JX**	Jiangxi	**TJ**	Tianjin	**GAS**	Natural gas products
GZ	Guizhou	**LN**	Liaoning	**XJ**	Xinjiang	**MAN**	Other manufacturing industries
HA	Henan	**NM**	Inner Mongolia	**YN**	Yunnan	**OIL**	Oil refining, cooking & nuclear fuels
HB	Hubei	**NX**	Ningxia	**ZJ**	Zhejiang	**OMN**	Minerals and other mining
EUR	Europe	**ROW**	Rest of the World	**ODC**	Other Developed Countries	**SER**	Services
USA	United States					**TRN**	Transportation and post
						WTR	Water

Household Types $\bar{h} \in H$					
hh1	Urban (China)	**hh2**	Rural (China)	**hh**	Undifferentiated (outside China)

Notes: Other Developed Countries include Australia, Canada, Japan, New Zealand and South Korea.

Table C2. Other sets, price and quantity variables

Symbol	Description
Sets	
$g \in G \supset J$	Sectors (commodity production, private and public consumption, investment)
$s \in INT \subset R$	International regions
$p \in CHN \subset R$	Chinese provinces
$nhw \in NHW$	Nuclear, hydro and wind generated electricity
$cgo \in CGO$	Coal, Gas, Oil generated electricity
$j \in ENE \subset J$	Energy commodities
$j \in FOF \subset ENE$	Fossil fuel commodities
$j \in NENE \subset J$	Non-energy commodities
Quantities and Prices	
Y_{gr}	Production index of sector g in region r
A_{jr}	Armington index of commodity j in region r
M_{jr}	Imports of commodity j in region r
YT	International transportation services
$W_{\bar{h}r}$	Welfare of consumer $\bar{h}$ in region r
P_{gr}	Domestic output price for sector g in region r
PA_{jr}	Armington price of commodity j in region r
PD_{jr}	Price of domestic composite of commodity j in region r
PM_{jr}	Price of imported composite of commodity j in region r
$PAT_{j,g,r}$	Tax and carbon price inclusive Armington price of j, input to sector g, in region r
PT	Price index of international transport services
$PS_{nhw,r}$	Resource price for nhw in region r
$PW_{\bar{h}r}$	Welfare index for consumer $\bar{h}$ in region r
PK_r	Capital rental rate in region r
PL_r	Wage rate in region r
PS_{jr}	Price for sector-specific resource for sector j in region r
P_r^{CGO}	Price of conventionally generated electricity in region r
$P_{nhw,r}$	Price of electricity of type nhw in region r
$INC_{\bar{h}r}^{C}$	Private income of consumer $\bar{h}$ in region r
INC_r^G	Government income in region r

Table C3. Elasticities of substitution

Symbol	Value	Description
σ_{ctop}	1.0	Top level private consumption (transport vs. non-transport consumption)
σ_{cntrn}	0.25	Energy vs. non-transport consumption composite
σ_{cene}	0.4	Energy composite in consumption
σ_{ccon}	0.25	Non-transport composite in consumption
σ_{gitop}	1.0	Top level public consumption/investment (energy vs. non-energy consumption)
σ_{giene}	1.0	Energy composite in public consumption/investment
σ_{ytop}	0.5	Top level (material vs. value added/energy inputs)
σ_{vae}	0.5	Value added vs. energy composite
σ_{kle}	1.0	Capital vs. labor and energy commodities
σ_{va}	1.0	Value added composite
σ_{ene}	0.5	Electricity vs. fuels composite
σ_{fof}	1.0	Fossil fuels in production
σ_{cgo}	5.0	Conventional fossil electricity production composite
σ_{nhwtop}	0.25	Top-level in NHW production (resource vs. value added and services composite)
$\sigma_{a,j}$	0.9 - 11.9	Foreign (M) vs. domestic (D) commodities
$\sigma_{o,j}$	0.9 - 11.9	Foreign, non-Chinese commodities
$\sigma_{c,j}$	1.8 - 30.9	Chinese commodities

Table C4. Other model parameters

Symbol	Description
$htax_{\bar{h}r}$	Direct tax from household to local government
$\overline{pat}_{jr}$	Tax-inclusive reference Armington price for commodity j
$\overline{pl}_{jr}$	Tax-inclusive reference price for labor in production j
$\overline{pk}_{jr}$	Tax-inclusive reference price for capital in production j
$\overline{ps}_{jr}$	Tax-inclusive reference price resources in production j
$\overline{psnhw}_{nhw,r}$	Tax-inclusive reference price resources in production nhw
$\overline{pm}_{jrr'}$	Tax-inclusive import price for commodity j shipped from region r to region r'
tl_{jr}	Labor use tax in production j
tk_{jr}	Capital use tax in production j
to_{jr}	Output tax for commodity j
ts_{jr}	Use tax for sector j specific resource
$tsn_{nhw,r}$	Use tax for sector nhw specific resource
te_{jr}	Export tax for commodity j
td_{jr}	Domestic tax rate for commodity j
tm_{jr}^{CHN}	Tax rate for imports of commodity j from provinces in China to region r
tm_{jr}^{INT}	Tax rate for imports of commodity j from international regions to region r
$c_{j\bar{h}r}^{\star}$	Min. consumption level (Stone-Geary parameter) of commodity j by household $\bar{h}$ in region r
$\theta_{\bar{h}r}^{W,SAV}$	Share of savings in top-level utility of household $\bar{h}$ in region r
$\tilde{\theta}_{\bar{h}r}^{W,CON}$	Share of consumption (net of min. consumption) in top-level utility of household $\bar{h}$ in region r
$\tilde{\theta}_{\bar{h}r}^{TRN}$	Exp. share (net of min. consumption) of transport in total exp. of household $\bar{h}$ in region r
$\tilde{\theta}_{\bar{h}r}^{CON}$	Exp. share (net of min. consumption) of energy commodities in non-TRN exp.
$\tilde{\theta}_{j\bar{h}r}^{CENE}$	Exp. share (net of min. consumption) of commodities j in total energy exp.
$\tilde{\theta}_{j\bar{h}r}^{CCON}$	Exp. share (net of min. consumption) of commodities j in total non-energy, non-transport exp.
$\theta_{r}^{G/ICON}$	Exp. share of energy commodities in government/investment exp.
$\theta_{jr}^{G/ICENE}$	Exp. share of commodities j in total energy exp. of government/investment sector
$\theta_{jr}^{G/ICCON}$	Exp. share of commodities j in total non-energy exp. of government/investment sector/
$\theta_{j'\,jr}^{TOP}$	Share of non-energy commodity j' in top-level production j
θ_{jr}^{RES}	Share of resources in top-level production j
θ_{jr}^{VAE}	Share of value-added cost in value-added/energy cost bundle in production j
θ_{jr}^{VA}	Share of labor cost in value added cost bundle in production j
θ_{jr}^{ENE}	Share of electricity in energy bundle in production j
$\theta_{j'\,jr}^{FOF}$	Share of commodity j' cost in fossil fuel bundle in production j
θ_{jr}^{A}	Share domestic (including local for China) commodity j in top-level Armington composite
θ_{jsp}^{M}	Share of j imports from s in total international imports of commodity j to province p
$\theta_{jp'\,p}^{D}$	Share of j imports from province p' in total domestic imports of commodity j to province p
θ_{jp}^{D}	Domestic share of j in total domestic and local composite of commodity j in province p

Notes: The production share parameters above are defined for commodities j ∈ {EIS, MAN, WTR, CON, TRN, SER, AGR, OMN}. For the remaining commodities, share parameters are defined analogously, but are omitted here for lack of space. Following the same logic, we omit the shares in the Armington aggregation for international regions.

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