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Alex L. Marten, Andrew Schreiber and Ann Wolverton

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Occupational Affiliation and the Incidence of Environmental Regulation[1]

Alex L. Marten, Andrew Schreiber[2], Ann Wolverton

National Center for Environmental Economics, U.S. Environmental Protection Agency

Abstract

We study the role of occupational heterogeneity in determining the economy-wide costs and incidence of regulation. The labor market represents an important pathway through which the costs of regulation are distributed, and empirical research has suggested that occupational heterogeneity is crucial to explaining labor market outcomes. However, most computable general equilibrium models used to assess the costs and incidence of energy and environmental policies assume a single labor type that can easily shift from one occupation to another, missing a potentially important characteristic of the labor market. We investigate the implications of labor market heterogeneity by modeling the limits it imposes on labor mobility and substitution in the supply and demand of occupations within a computable general equilibrium model. We use this framework to evaluate the social costs and incidence of a suite of large illustrative environmental regulations. We find that occupational heterogeneity, and its impacts on labor mobility, has limited implications for aggregate social costs but plays a key role in understanding how those costs are distributed across households. Depending on the composition of compliance activities, accounting for occupational heterogeneity can shift the burden of regulatory costs from high-income to low-income households or vice versa.

Keywords: environmental regulation, occupation, incidence, general equilibrium

JEL Classification: Q52, C68

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[2] Corresponding author: schreiber.andrew@epa.gov. 1200 Pennsylvania Ave NW, Washington, D.C., 20004.

1 Introduction

Economists have long studied the effects of skill-biased technological change on the labor market. Recent papers have been particularly concerned with how these types of shocks contribute to increasing wage differentiation across occupations. Theoretical and empirical evidence suggests that limits on occupational mobility among the relatively unskilled, at least in the short run, have played an important role in wage and job polarization in the United States over the past several decades (Acemoglu and Autor, 2011; Cortes, 2016). Occupational affiliation has also been shown to be important for estimating the impacts (Carrico and Tsigas, 2014) and incidence of trade policies (Artuc and McLaren, 2015). We contribute to this literature by examining how much occupational heterogeneity matters for estimates of costs and incidence of government regulations imposed on the firm, such as a more stringent energy or environmental standard or requirements to improve worker safety.

Like trade policies, these types of regulations also potentially favor certain types of skills over others. When a regulation shifts the demand for workers of a given occupation, how easily workers can move in or out of that occupation will determine relative wage effects. Similarly, how easily firms can shift workers in given occupations across tasks or perform those tasks with capital will, in part, determine the shift in demand for those occupations. The occupational flexibility of firms and households may therefore be critical in determining the share of regulatory costs passed on through wages. It has already been shown that accounting for the impacts of energy or environmental policies on household income sources is critical for estimating the incidence of regulatory costs and requires a general equilibrium framework (Fullerton and Heutel, 2010; Rausch et al., 2011; Marten, 2019). However, the role of occupational heterogeneity in determining how regulations affect households via the labor market remains an open question.

Because factors of production are at least somewhat mobile across sectors and space, estimating the incidence of regulations inclusive of the income effects requires a general equilibrium framework. We use a computable general equilibrium (CGE) approach to evaluate the impacts of regulation on households in the presence of occupational heterogeneity. To our knowledge, the role of occupational affiliation in determining the incidence of the types of regulations typically promulgated in the U.S. to implement environmental and energy policy goals has not yet been studied in this context. Most CGE models of the U.S. economy represent the labor market with full employment, instantaneous and costless adjustment, and a single type of worker (U.S. EPA, 2018). Building from the theoretical general equilibrium framework of Cortes (2016) and Jung and Mercenier (2014), we extend the CGE model of Marten and Garbaccio

(2018) to incorporate three broad occupation types based on the skill level and types of tasks performed (i.e., non-routine manual, routine, and non-routine cognitive).

To represent the occupational mobility on the supply side we implement a novel approach that allows for asymmetric costs to workers of switching occupations based on what has been observed in the empirical literature. Specifically, we model occupational switching as a Constant Ratio of Elasticity of Transformation, Homothetic (CRETH) function where the wage impacts of switching occupations are calibrated to the empirical estimates of Cortes (2016). Labor substitution possibilities on the production side are modeled following the approach often applied in the labor and trade literature (Jung and Mercenier, 2014; Carrico and Tsigas, 2014; Cortes, 2016). Capital and routine labor are treated as substitutes in production, since routine occupations are, by definition, those jobs that require tasks that are algorithmic and could be done by machines instead of humans. Alternatively, tasks performed by non-routine occupations are considered complements to routine labor and capital. Combining data from Bureau of Labor Statistic's Occupational Employment Statistics and Census Bureau's Current Population Survey we disaggregate sectoral and regional labor demand by occupation as well as household labor supply by region and income quintile. We also develop an estimation framework for adjusting value-added substitution elasticities to accommodate the modified production structure.

Since environmental regulations have historically outnumbered many other types of economically significant Federal regulation in the U.S.,[3] we examine the role of occupational heterogeneity in determining the level and distribution of social costs from 1990 Clean Air Act Amendments (CAAA), requirements imposed on the manufacturing sector as an illustrative case study. Specifically, we consider the set of manufacturing sector abatement activities required for compliance with regulations promulgated through 2005 under the CAAA and evaluated by the EPA (2011). The focus on the manufacturing sector allows us to consider the role of regulation in exacerbating or ameliorating the impact on the routine occupations that have been disproportionately impacted by changes in technical progress and trade patterns. There is uncertainty as to the required inputs for regulatory compliance activities, so we consider a range of bounding cases to illustrate the potential impacts of occupational heterogeneity and highlight the need for more research and data on the input composition of regulatory compliance.

[3] Historically, regulations for which annual costs or benefits exceed $100 million in any given year have been deemed economically significant by the Office of Management and Budget. The threshold for economic significance was increased to $200 million in 2023. See https://regulatorystudies.columbian.gwu.edu/economically-significant-rules-agency for more information on regulatory activity over time and by Federal agency.

We find that accounting for occupational affiliation has a negligible effect on overall welfare estimates. However, due to the heterogeneity in occupations across income quintiles, changes in wage differentials induced by regulations promulgated under the CAAA can have a significant effect on the incidence of regulatory costs. We find that under capital-intensive compliance requirements the upward pressure on routine occupation wage rates due to substitution effects more than offsets decreases in employment due to economic contraction. These occupations are predominately supplied by low- and middle-income households, thus dampening source side impacts and reducing their regulatory costs by 5%-10%. When compliance activities are labor-intensive the effect of occupational heterogeneity on the incidence of regulatory costs is determined by the types of occupations required for compliance. When compliance requires predominantly high-skilled non-routine cognitive occupations, the regulatory costs borne by the highest income quintile can fall by over 150% with similar increases for the low- and middle-income quintiles. The opposite holds for regulations that require predominantly routine labor for compliance, suggesting that occupational affiliation a key component in determining the incidence of regulation, depending on the inputs required for compliance.

The remainder of the paper is organized as follows. Section 2 discusses the literature on the role of occupational affiliation and labor markets on policy impacts. Section 3 describes the CGE models and the stylized regulations scenarios. Section 4 presents the results of our regulatory simulations that include a series of sensitivity analyses. Section 5 concludes.

2 Background

The empirical trade literature has long been concerned with how trade liberalization affects U.S. workers. Artuç, et al. (2010) estimate the cost of moving across industries in response to changes in trade policy. The estimation strategy is predicated on a simple theoretical model in which workers can change jobs across industries but pay a cost when they do so. The moving costs are made up of a time- and worker-invariant component and a time-varying idiosyncratic component. Artuç, et al. estimate moving costs that are several times higher than the average annual wage. Because they are so large, they find that the labor market adjusts slowly to trade liberalization. Workers in the sector that directly competes with imports experience a large loss in wages, but because of the idiosyncratic component of moving costs it is possible that some workers in this sector may actually benefit.

Building on the work of Artuç, et al. (2010), Artuç and McLaren (2015) estimate the costs of moving when workers can change both industry and occupation. While they find that the cost of switching industries does not differ substantially by worker background, this is not the case for switching occupations. For instance, it is costlier for a non-college educated worker to enter a high-skilled occupation than it is for a college-educated worker. They find that industry affiliation is the primary determinant of whether a worker is harmed by trade liberalization, but occupational affiliation is the key driver of distributional effects from offshoring: workers with less education are most likely to experience a decline in wages, while college-educated workers are most likely to benefit.

Papers in the labor literature also have explored the role of occupational affiliation in how the labor market responds to exogenous shocks. Acemoglu and Autor (2011) examine the effects of skill-biased technological change (driven by the rapid increase in the productivity of information and communication technologies and processing devices) on workers. In this context, middle skill occupations (e.g., clerical, production, sales) perform tasks that are more susceptible to "routinization."[4] In addition, increased reliance on automation and offshoring of routine tasks raises the relative demand for workers who perform complementary non-routine tasks, either cognitive tasks associated with relatively high skill occupations (e.g. technical, professional, managerial), or difficult to routinize manual tasks associated with relatively low skill occupations (e.g., health care, services).[5]

With limited opportunities for middle-skill workers to shift into high skill occupations, particularly in the short run, Acemoglu and Autor (2011) observe a growing wage premium between skilled and unskilled workers in the United States over the last three decades: rising wages associated with non-routine, cognitive occupations for workers with post-graduate degrees and large decreases in wages for less educated workers. Wage polarization during this period also was accompanied by job polarization: the share of high skill (high wage) and low skill (low wage) occupations in overall employment grew, while growth in employment for middle-skilled occupations not only consistently lagged the economy-wide average but continued to slow each decade. Acemoglu and Autor (2011) find that, because of job

[4] As previously mentioned, these tasks are procedural, rule-based activities that can be executed more cheaply and quickly by a machine instead of a person after the shock.
[5] Motivated by the Kuznets curve and labor literatures, Duernecker and Herrendorf (2017) construct an analytic model to examine how technological change has affected both sectoral and sectoral composition for 67 countries.

polarization and the difference in the tasks inherent in different types of occupations, occupational affiliation rather than industry has been the driving determinant of wages.[6, 7]

Cortes (2016) estimates a wage equation where an individual's potential wage at a given time and skill level is determined by a common occupation-specific premium and individual-specific productivity in an occupation. He finds that the highest ability workers are more likely to switch out of routine jobs. The probability of switching to nonroutine manual jobs is decreasing in ability, while the probability of switching to nonroutine cognitive jobs is increasing in ability. For non-routine workers, low-ability workers are much more likely to switch occupations and tend to switch into routine jobs (vs. switching the type of nonroutine job they do). Workers who switch from routine to nonroutine manual jobs have significantly lower wage growth than stayers over the short run (14% lower) but have significantly faster wage growth than stayers in the long run (5%–12% higher). Workers who switch from routine to nonroutine cognitive occupations have significantly higher wage growth than stayers in both the short and long run (6%–12% and 14%–16% higher, respectively).[8]

Domestic regulations that require firms to comply with energy, environment, or worker safety requirements are typically much smaller in magnitude than the macroeconomic trends that have led to increasing wage polarization in the U.S. economy. However, because they potentially favor certain types of skills over others, these types of standards may also affect the wage differential in ways that substantively impact households. This is particularly important since it has been shown that accounting for the impact of policies on sources of income (e.g., labor and capital earnings) is critical for understanding how the costs are transmitted to households (Fullerton and Huetel, 2010; Rausch et al., 2011). Marten (2019) demonstrated that on the source side regulatory costs are passed onto the primary factors (i.e., labor, capital, natural resources) that are the least mobile. In that work, natural resources and the existing capital stock were the factors with the most limited mobility, and in turn owners of those resources were estimated to bear a significant share of the regulatory costs. Because labor was assumed

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[6] Educational attainment – which is correlated with cognitive and non-cognitive skills ability - also has historically been an important predictor. The authors find that for the post 1979 period occupation initially has less explanatory power than education but performs better in later years. As anticipated, industry dummies perform less well.

[7] Roys and Taber (2011) identify wage changes between occupations due to technological change versus changes in the distribution of skills within an occupation. They find that technological change within and between occupations each explain about half of the increasing wage inequality since 1979. Shifts in the skill composition of workers within an occupation did not play an important role. See also Cunha, et al. (2011) and Oreopoulos and Petronijevic (2013).

[8] Workers that stay in routine occupations have significantly lower wages than stayers in other occupations: the wage premium for routine occupations fell by an estimated 17% between 1976 and the mid-2000s relative to nonroutine manual occupations. The wage premium for nonroutine cognitive occupations rose by an estimated 25% relative to the wage premium for nonroutine manual occupations.

to be perfectly mobile between sectors, occupations, and across space within a large geographic region, workers bore little of the regulatory costs.

Moving away from an assumption that labor is undifferentiated and perfectly substitutable across occupations may offer additional insights into the distributional implications of regulation. Table 1 describes the share of job transitions between aggregate occupational categories based on the Current Population Survey's (CPS) annual economic supplement from 2007-2016. Following Stewart (2002), a job change is recorded if an observation had multiple employers in the previous year, more than one spell of unemployment in the previous year or had a change in major industry.[9] Most job changes occur within the aggregate occupational category with little cross-occupational movement towards higher paying non-routine cognitive jobs that have higher skill and educational requirements. More common are transitions across manual and routine occupations that are typically less skilled with lower educational requirements. This suggests that occupational choice, broadly defined, is a relatively inflexible component of labor supply decisions and a potentially important aspect of quantifying the distributional impacts of regulation. Similar tables for transitions between aggregate sectors and Census divisions are reported in Appendix A. The data suggests that transitions between sectors are more common than across occupations and transitions between regions are less common.[10]

Table 1: Occupational Transition Matrix

		Destination		
		Non-Routine Cognitive	Non-Routine Manual	Routine
Origin	Non-Routine Cognitive	0.911	0.022	0.067
	Non-Routine Manual	0.038	0.807	0.154
	Routine	0.046	0.058	0.896

[9] In the CPS, concurrent employment by multiple employers is treated as one job, such that multiple employers would signal a job change. While a job change could also be associated with one unemployment stretch, from the CPS data it is not possible to identify if a single stretch occurred at the beginning of the previous year and the person was employed in the same position between that unemployment stretch and the subsequent March survey. Transition shares are calculated by dividing the number of observed transitions between occupational types by the total number of transitions away from an origin occupation (summing across columns equals unity). For instance, 91% of workers leaving a non-routine cognitive job find a new job with a similar occupation whereas only 2% move from a non-routine cognitive job to a non-routine manual position.

[10] Sectoral transitions were calculated using CPS data as in occupational transitions in Table 1. Regional migrations due to job transitions are calculated from the Origin-Destination Job-to-Job dataset published by the Census Bureau (see Hyatt et al. 2014). Transition shares correspond to all recorded transitions from 2010-2015.

In CGE models, labor and capital typically enter the production function as substitutes with no differentiation by skill or occupation, with a few notable exceptions. For instance, in USAGE, a dynamic CGE model of the United States, employed labor is differentiated by industry, occupation, and region and is not perfectly substitutable across all categories. Switching occupations is assumed to incur a cost, and that cost is assumed to increase with the degree of dissimilarity between the current and destination occupation along specific characteristics (Dixon and Rimmer, 2002). The model relies on historical data to parameterize permanent transitions in and out of the labor force and assumes restrictions on occupational mobility and length of unemployment spells. Recently, this model has been used to evaluate the impact of illegal migration (Dixon, et al., 2011) and as a basis for the labor market module in USAGE-TERM, the multi-regional counterpart designed to analyze trade policies (Dixon and Rimmer, 2018).

In related work, Carrico and Tsigas (2014) compare trade-based simulation scenarios across the default version of the static Global Trade and Analysis Project (GTAP) model with two labor types (skilled and unskilled) and an extended version with additional occupational detail in the United States. The version with the extended labor market expands the labor type classifications to 22 based on employment and wage data from the U.S. Bureau of Labor Statistics' (BLS) Occupational Employment Statistics (OES) survey and the Agricultural Census. The labor supply for each occupational category is assumed to be fixed. Carrico and Tsigas (2014) compare the results of the default model to two variants of the extended version. The first variant uses the default substitution elasticities between labor, land, and capital and the second features a modified production structure allowing greater substitution between low wage occupations and other factors (capital and land) and relatively less substitution with higher wage occupations. The authors find small differences between the default and extended version of the model when the standard GTAP elasticities are used in both cases. When they use the more realistic alternative substitution assumptions in line with labor theory, they find wage impacts that are larger in absolute value reflecting the reduction in firms' ability to substitute across occupations when responding to the trade policy and its effects.

The potential employment effects of environmental and energy policies on the economy are often raised as a concern of policy makers and stakeholders. The literature has responded with several efforts to better assess the economy-wide labor market impacts of these types of policies. These efforts have integrated a more nuanced labor market into CGE models, either by incorporating reduced-form involuntary unemployment, or by more explicitly modeling the wage-bargaining process. We briefly describe these approaches below. However, these literatures mainly focus on changes to the unemployment rate due to environmental or energy policies. To our knowledge, none of these papers introduce occupational heterogeneity into their models or study the incidence of social costs across income and location.

A relatively common approach to introducing involuntary unemployment into CGE models is through a wage curve, based on the empirical observation that real wages are a decreasing function of the unemployment rate (Blanchflower and Oswald 1994). This approach effectively shifts the labor supply curve inward creating a wedge between the quantity of labor demanded and the quantity supplied.[11] While this approach is broadly consistent with the idea that frictions in the labor market prevent wages from adjusting to their market-clearing level, involuntary unemployment is exogenously determined in the model based on a highly-simplified, reduced-form approach (Bohringer, et al 2005). Several studies have used the wage curve approach to consider unemployment effects in the context of environmental or energy policy (e.g., Dissou and Sun, 2013; Rivers, 2013; Bohringer et al., 2001; Bohringer et al., 2012; Bohringer et al., 2013; and Castellanos and Huetel, 2023).[12]

The second strand of literature explicitly includes various wage-setting mechanisms in a CGE model, including efficiency wages, collective wage-bargaining, job search and matching models, as well as explicit incorporation of other types of wage rigidities.[13, 14] Babiker and Eckaus (2007) add two labor rigidities for a single representative agent in each region of their CGE model. For the first rigidity, an exogenously determined fraction of sector-specific labor is not allowed to leave that sector in each timestep. For the second rigidity, nominal wages for sector-specific labor are fixed at the same level as in the initial timestep. As a result of these rigidities, a policy can induce an excess supply of sector-specific labor and a positive

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[11] When implementing this approach, the equilibrium wage is at the intersection of the labor demand and wage curves, and equilibrium employment is determined by the intersection of the labor supply curve and the equilibrium wage.

[12] Dissou and Sun (2013) use a static model for Canada with skilled and unskilled labor and compute changes to unemployment rates and welfare but do not distinguish households based on income and region.

[13] Researchers have used explicit wage-setting mechanisms in CGE models for other applications. With respect to tax reform in Europe, Hutton and Ruocco (1999) include an endogenous choice between part-time and full-time employment and introduce involuntary unemployment through an efficiency wage model for full-time workers. Bettendorf, et al. (2009) and Bohringer, et al. (2005) assume wages are determined by firm–union bargaining. In addition, Bohringer, et al. (2005) assume that "each additional unit of labor is first unemployed for a certain period and may then be combined with a job according to a stochastic matching process."

[14] The efficiency wage model is based on the idea that employers can increase worker productivity by paying above-market wages. In the collective wage-bargaining model above-market wages result from negotiations between firms and trade unions with some market power. Job search-and-matching models assume that finding a job requires time and effort and is inherently stochastic. The higher the ratio of unemployed to vacancies, the lower the probability of finding a job. See Boeters and Savard (2013) for discussion of different models of unemployment and calibration issues encountered when incorporating them into a CGE model.

rate of unemployment. The rigidities also increased costs above those for the same policy in a model without rigidities.

Other studies have incorporated components of job search and match models into a CGE framework. Balistreri (2002) considers labor supply as a function of the foregone reservation wage and an individual's chance of not being matched to a job, where the probability of a successful match is itself affected by the aggregate behavior of other agents in the model. He finds that changes in unemployment are most sensitive to turnover rates, elasticities for leisure, and wage markups and rigidities in labor mobility. Castellanos and Heutel (2023) also develop a methodology for incorporating search and matching into a CGE framework to analyze unemployment impacts from climate policies.

Shimer (2013) incorporates search costs and unemployment into a stylized two sector general equilibrium model to characterize the optimal tax rate on the dirty good. The cost of searching for a new job in the clean sector combined with human capital specific to the production of only one of the two goods manifests as a loss of productivity when the worker switches jobs. Shimer finds that including search costs in the model affects how workers respond to the tax, resulting in differential effects on workers across the two sectors, but that this does not change the optimal level of the tax on the dirty good.

Most of the previous studies model aggregate labor transitions due to unemployment in a static framework or with multi-year time steps. Hafstead and Williams (2018) develop a two-sector CGE model that incorporates several wage-setting mechanisms where the adjustment costs from transitioning between unemployment and employment are realized at a much smaller time step. The model allows for involuntary unemployment due to search frictions. Unemployed workers can search for jobs in both sectors. The rate at which firms hire workers is a function of the ratio of aggregate recruiting effort in that sector to the number of unemployed workers. The higher the recruiting effort and the larger the number of workers searching for a job within a sector, the higher the probability of a match. They use a Nash bargaining process where workers are compensated at a rate equal to the opportunity cost of not searching for another job. The easier it is for a worker to find another job, the higher the compensation to induce them to stay. However, higher recruiting efforts in one sector reduces the probability of a match in the other sector – and those workers' bargaining power - due to competition for workers. The authors find that the net unemployment impacts of environmental policy are small due to the offsets in labor demand by unregulated sectors.[15]

[15] Hafstead et al., (2022) extend the model in Hafstead and Williams (2018) to a 22 sector CGE model but where labor and materials are the only inputs to production.

While Hafstead and Williams (2018) focus on the short run temporal transition costs of unemployment in a nationally representative aggregated model periods of unemployment and subsequent job searching can also induce workers to physically move. While not considering general equilibrium feedbacks, Kuminoff et al. (2015) use a spatial equilibrium sorting model to demonstrate the welfare impacts of environmental regulation that affects individuals' choices on where to live and work. Assuming a fixed number of layoffs directly induced by a regulation, they find that the resulting welfare changes are based on lost human capital, wages and relocation expenses. An application in Northern California reveals a large portion of the reduction in annual earnings are due to lost job-specific human capital.

While these studies are important for understanding the near-term costs of unemployment due to regulations, they focus on relatively short-run frictions in the labor market that prevent instantaneous adjustment in response to a new shock. Our focus is on the role that imperfect substitution and differential skill levels across occupations have on firm and household responses to a new policy. In this case, the "friction" or cost is driven by the fact that labor of one type is less effective in the new occupation than it was in the one in which it was originally employed. Thus, we continue to rely on a CGE model with longer time steps since our aim is to characterize the medium to long run incidence of regulation.

3 Methods

The most common approach to estimating the social cost of a regulation in a general equilibrium setting is using a computable general equilibrium (CGE) model. CGE models assume that during a discrete period of time an economy can be characterized by a set of conditions in which supply equals demand in all markets. When a government policy, such as a tax or a regulation, alters conditions in one market, a general equilibrium model determines a new set of relative prices for all markets that return the economy to equilibrium. These relative prices determine changes in sector outputs, demand for factors of production, intra-national and international trade, investment, and household consumption of goods, services, and leisure (U.S. EPA, 2010). As such, a CGE model is also able to capture the distribution of regulatory costs through multiple economic channels. We describe the general structure of the CGE model we use to examine the cost and incidence of regulation in Section 3.1, how we model occupational heterogeneity in Section 3.2, and how we model illustrative regulations in Section 3.3.

3.1 Model

We modify version 1.2.0 of the SAGE model to account for occupational heterogeneity.[16] SAGE v. 1.2.0 is an inter-temporal CGE model of the U.S. economy covering the period 2016 through 2061 and is resolved at a subnational level. The model is similar to the class of calibrated CGE models regularly used to analyze environmental and energy policies (e.g., Caron and Rausch, 2013; Chateau et al., 2014; Ross, 2014). In this section, we provide a general description of the version of the SAGE model used in this paper. Marten and Garbaccio (2018) and Marten et al. (2023) provide detailed technical documentation of the model.

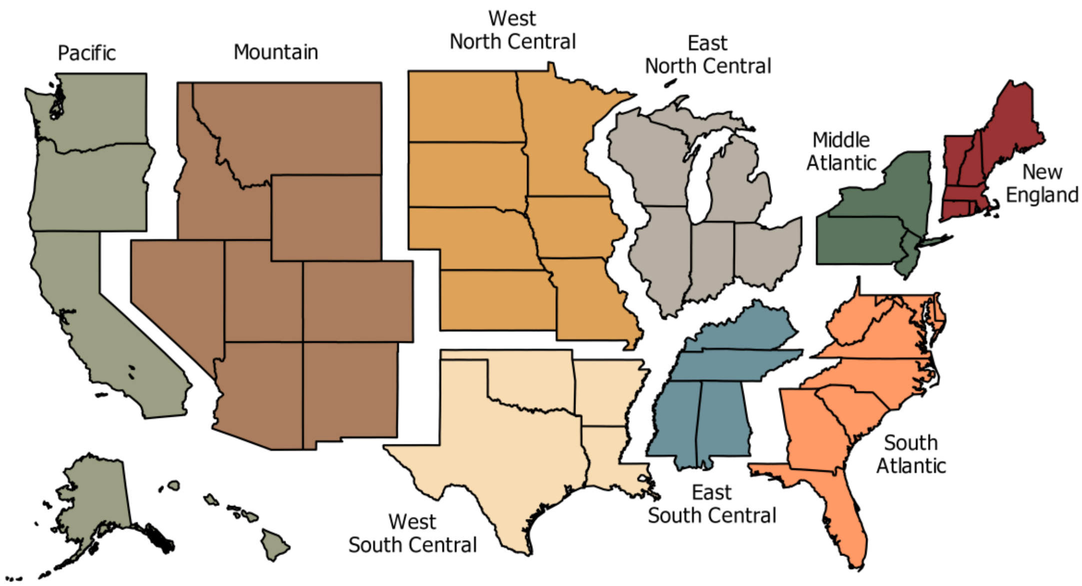

Figure 1: SAGE Regions

The model represents the nine Census regions of the United States (Figure 1). Labor is immobile across regions, though we explore the implications of this assumption for our results later in the paper. Capital is also immobile once it is installed, though savings/investment is mobile across regions. Trade in goods follows an Armington specification, where goods are differentiated by origin (Armington, 1969). While the price of foreign exchange is endogenously determined, international demand and supply are perfectly elastic following the small open economy assumption.

[16] We use a recursive naming convention: SAGE stands for SAGE is an Applied General Equilibrium (SAGE) model. The model has been updated since version 1.2.0 (see Marten et al., 2023) to incorporate additional baseline information on the international and government accounts, a large open economy representation, and sector differentiated productivities. We rely on version 1.2.0 to keep the baseline characterization relatively simple, which allows for greater ease of interpretation as we introduce nuance into the labor market specification.

Within each region, production is disaggregated into 23 sectors, with a focus on manufacturing and energy sectors that are often the focus of environmental regulation at the federal level (Table 1). In most sectors, production is assumed to be constant returns to scale and is defined by a nested CES function (Figure 3). Firms make decisions about the relative use of value-added primary factors (i.e., capital and labor) and energy, and then the relative use of other intermediate material inputs compared to the energy and value-added composite. The energy good is a composite of primary energy sources (i.e., coal, natural gas, and refined petroleum products) and electricity. It is assumed that firms determine the relative use of primary energy sources followed by the relative use of primary fuels compared to electricity. The sub-nest combining non-energy intermediate inputs is assumed to be Leontief. Since labor is an integral part of the value-added component this part of the production function is described further in Section 3.2.1.

Table 2: SAGE Sectors

Manufacturing		Energy	
bom	Balance of manufacturing	col	Coal mining
cem	Cement, concrete, & lime manufacturing	cru	Crude oil extraction
chm	Chemical manufacturing	ele	Electric power
con	Construction	gas	Natural gas extraction & distribution
cpu	Electronics and technology	ref	Petroleum refineries
fbm	Food & beverage manufacturing		
fmm	Fabricated metal product manufacturing	Other	
pmm	Primary metal manufacturing	agf	Agriculture, forestry, fishing & hunting
prm	Plastics & rubber products	hlt	Healthcare services
tem	Transportation equipment	min	Metal ore & nonmetallic mineral mining
wpm	Wood & paper product manufacturing	srv	Services
		trn	Transportation
		ttn	Truck transportation
		wsu	Water, sewage, & other utilities

Sectors associated with fixed factor inputs, such as land or natural resources, have a production structure that deviates from the one presented in Figure 3. The presence of a fixed factor suggests that the production function in those sectors should exhibit decreasing returns to scale to more accurately represent the responsiveness of production to changes in relative prices. Therefore, in the resource extraction sectors (col, gas, cru, and min) and the agriculture and forestry sector (agf) we include an additional top-level nest which combines the fixed factor with the capital-labor-energy-materials (KLEM) composite. The substitution elasticity between the fixed factor and KLEM composite is calibrated, so that the price elasticity of supply in these sectors matches empirical estimates.

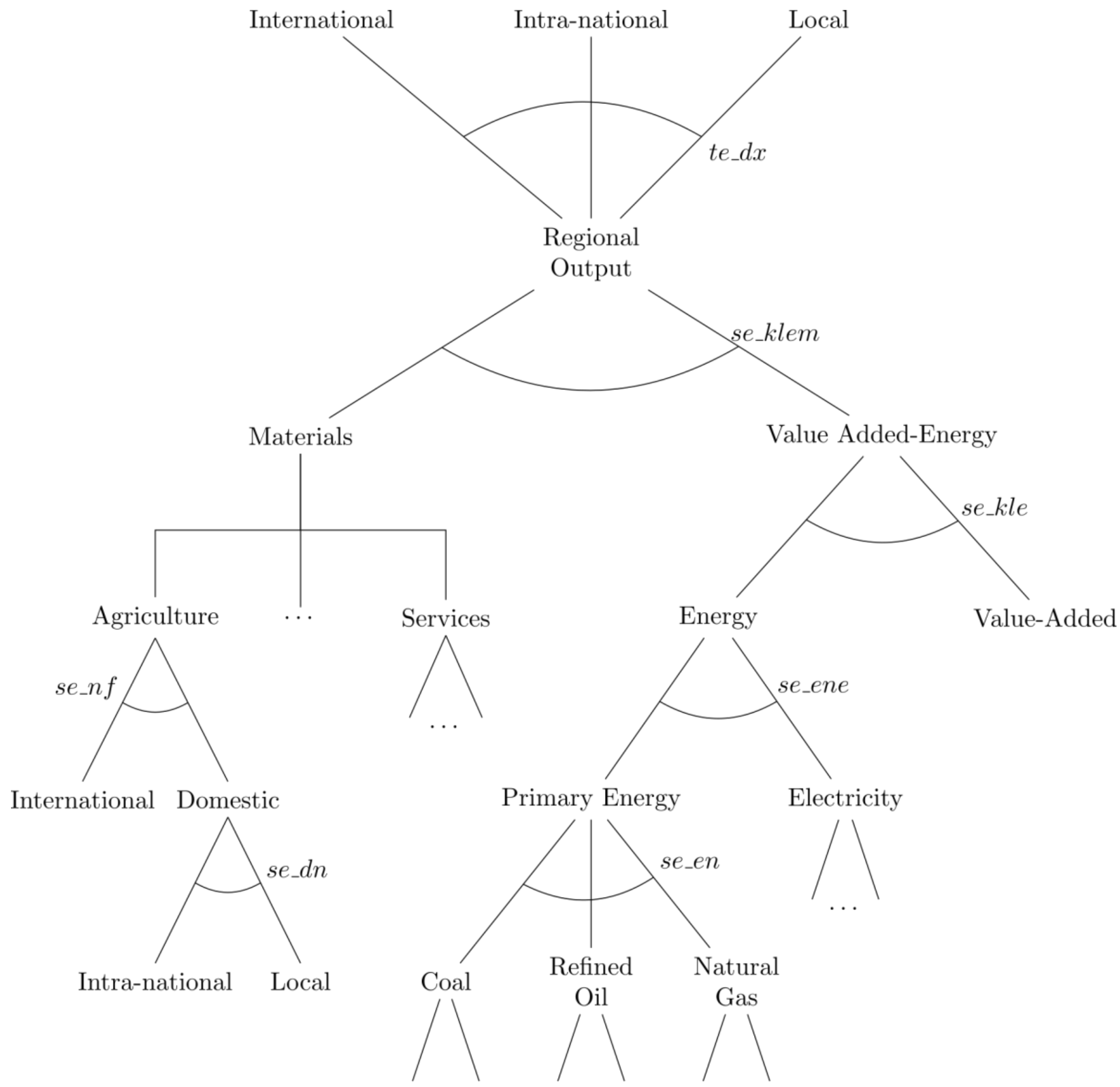

Figure 2: General Production Structure

Within each region, SAGE also models five representative households based on their pre-tax money income level in the initial year of the model (Table 3).[17] The income groups are selected to match U.S. income quintiles at a national level as closely as our underlying data source allows. Each representative household is assumed to maximize inter-temporal per capita welfare subject to a budget constraint and conditional on initial endowments of capital, fixed factor resources, and time. The inter-temporal welfare

[17] Money income includes cash-based transfer payments (e.g., Social Security and the Supplemental Nutrition Assistance Program). Non-cash-based transfer payments (e.g., Medicare and Medicaid) are included in consumption.

function is an isoelastic utility function (i.e., constant relative risk aversion), while intra-temporal preferences are modeled as a nested CES function (Figure 3).[18]

Table 3: SAGE Households

Household	Benchmark Year Income [2016$]
hh1	< $30,000
hh2	$30,000 - $50,000
hh3	$50,000 - $70,000
hh4	$70,000 - $150,000
hh5	> $150,000

The nested structure of the intra-temporal utility function treats energy and materials in a similar fashion to the standard production function. Households choose their relative consumption of primary energy sources before selecting the ratio of primary energy to electricity. The energy bundle is then traded off against non-transportation final consumption goods, a bundle that is then traded off against transportation. At the top level of the intra-temporal utility function the ratio of consumption to leisure is selected. In Section 3.2.2 we describe how time not spent as leisure is transformed into time engaged in different occupations.

The inter-temporal connection between periods in the model occurs through the capital stock carried over from one period to the next. The growth of the capital stock is a function of the depreciation rate and endogenously determined investment. We assume a partial putty-clay specification for capital to represent the mobility of extant capital across sectors. Production associated with existing capital at the start of the model's time horizon is modeled as Leontief based on the initial year's cost shares, while production with new capital has the substitution possibilities afforded in a nested CES structure (Figure 3). New capital stock is considered perfectly mobile across sectors, while existing capital has limited and costly mobility as captured by a CET function that supplies extant capital across sectors.

SAGE has a single government agent representing all jurisdictions. The government raises revenue through ad valorem taxes on capital, labor, production, and consumption. Real government expenditures grow at the balanced growth rate based on population and productivity growth. The government balances its budget through lump sum transfers.

[18] Households are differentiated based on income sources and consumption expenditures. Substitution elasticities within the households' utility functions are assumed to be the same across the representative households.

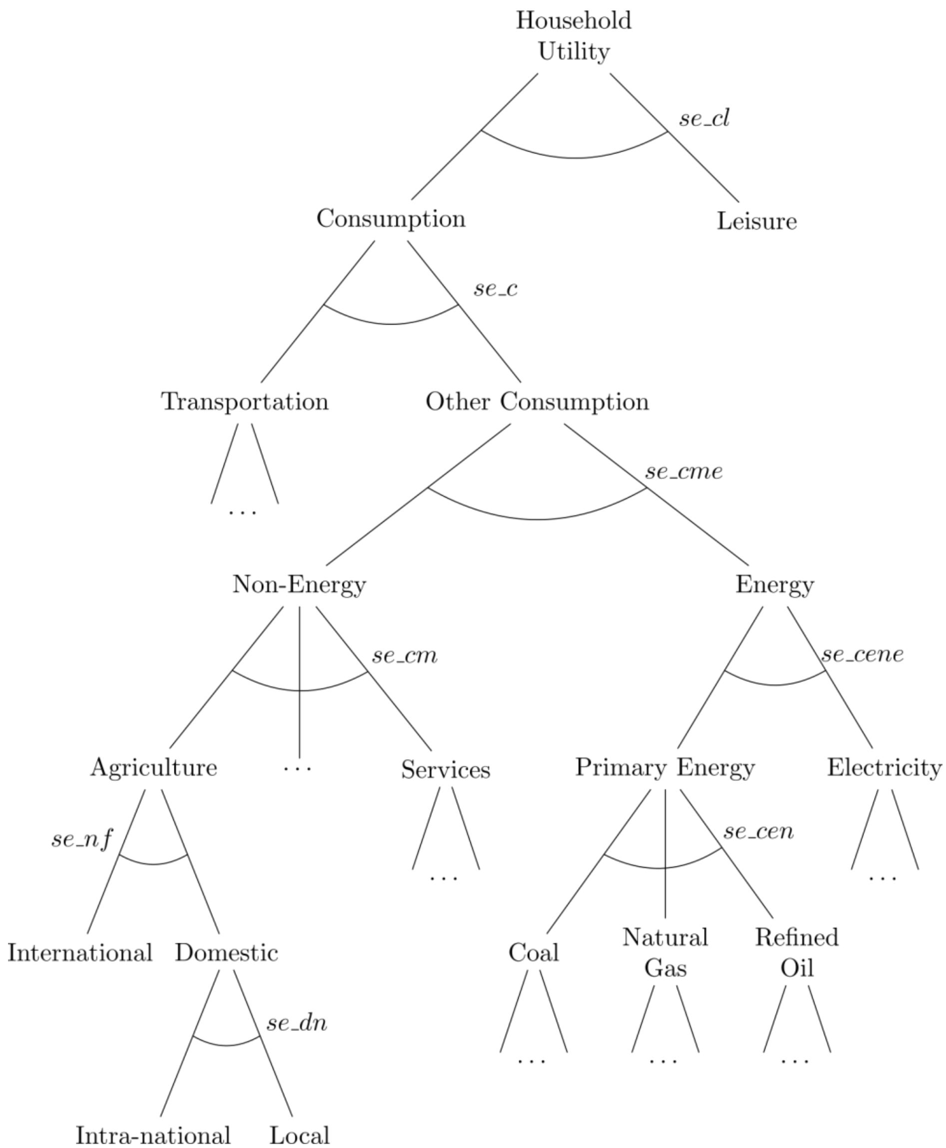

Figure 3: Household Preferences

There are three main types of inputs to the model: (1) the social accounting matrix describing the state of the economy in the initial year; (2) substitution elasticities that define opportunities to move away from the structure observed in the initial year; and (3) parameters defining the expected evolution of the economy in the baseline. These inputs are described in Appendix B.

We solve the model as a mixed complementarity problem (MCP) following Mathiesen (1985) and Rutherford (1995). The MCP approach represents the model as a series of zero-profit conditions, market clearance conditions, budget constraints, household first-order conditions, and closure rules. The problem is formulated in the General Algebraic Modeling System (GAMS).[19] The MCP is solved using the PATH solver (Ferris and Munson, 2000).

3.2 Modeling Occupation Heterogeneity

Like most CGE models, the default version of SAGE treats labor as homogenous and assumes a single labor market in each region. Households supply labor, which firms then combine with capital in a value-added sub-nest (Figure 4). The elasticity of substitution between labor and capital is denoted as *se_kl*.

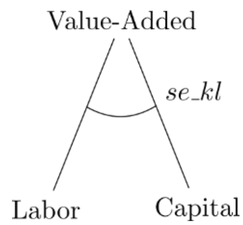

Figure 4: Default Value-Added Nest with Homogeneous Labor

To incorporate occupational heterogeneity we borrow the general framework from Cortes (2016). On the household side, he assumes a single representative household composed of a continuum of workers with different skill levels. High skilled workers are more productive at all tasks and particularly productive at the more complex tasks associated with nonroutine cognitive occupations (nonroutine manual tasks are the least complex). Workers endogenously sort into one of three occupations (i.e., nonroutine manual, routine, and nonroutine cognitive). Real wages – measured as wages per efficiency unit multiplied by the number of efficiency units supplied – are lowest in nonroutine manual jobs and highest in nonroutine cognitive jobs. In equilibrium, the least skilled workers sort into nonroutine manual occupations, middle skilled workers sort into routine occupations, and highly skilled workers sort into nonroutine cognitive occupations where the marginal worker has no incentive to switch occupations. There is no cost transaction cost to switching jobs. On the producer side, Cortes (2016) assumes that services require only nonroutine manual tasks as an input, while manufacturing goods consist of both routine and nonroutine cognitive tasks. Routine tasks require labor and physical capital, while nonroutine cognitive tasks can only be performed by labor. Thus, capital is a substitute for routine labor and a complement to nonroutine cognitive labor.

[19] GAMS Development Corporation. General Algebraic Modeling System (GAMS) Release 24.2.3. Washington, DC.

As the above description makes evident, incorporating occupational heterogeneity requires disaggregating both labor demand and supply by occupation. We describe our modeling approach for labor demand by occupation in Section 3.2.1 and labor supply by occupation in Section 3.2.2.

3.2.1 Labor Demand Specification

Labor demand by sector and region is disaggregated by occupation using the OES state level data by the BLS. We follow Cortes (2016) to map the 22 major Standard Occupational Classification (SOC) categories into the three broad occupations: routine (r), non-routine manual (m), and non-routine cognitive (c).[20] The mapping is presented in Table 4. Using the mean annual wage and total employment statistics, the wage bill by occupation, sector, and state is computed from the OES dataset. The wage bill by occupation is then aggregated to the SAGE sectors and regions. The share of the wage bill by occupation for each sector is used to disaggregate the SAGE regional and sectoral benchmark labor demand.[21] Across all sectors, roughly 48% of reference labor demand is attributed non-routine cognitive occupations, 40% to routine occupations and the remaining 12% to non-routine manual occupations.

Table 4: Occupation Mapping from Major SOC to SAGE Classification

SOC	Description	SAGE Occupation
11	Management Occupations	c
13	Business and Financial Operations Occupations	c
15	Computer and Mathematical Occupations	c
17	Architecture and Engineering Occupations	c
19	Life, Physical, and Social Science Occupations	c
21	Community and Social Service Occupations	c
23	Legal Occupations	c
25	Educational Instruction and Library Occupations	c
27	Arts, Design, Entertainment, Sports, and Media Occupations	c
29	Healthcare Practitioners and Technical Occupations	c
31	Healthcare Support Occupations	m
33	Protective Service Occupations	m
35	Food Preparation and Serving Related Occupations	m
37	Building and Grounds Cleaning and Maintenance Occupations	m

[20] The major SOC code for sales and related occupations (SOC 41) contains first line supervisors of sales workers. Cortes (2016) considers these occupations to be nonroutine cognitive occupations (c), whereas the remainder of SOC 41 occupations are considered routine occupations (r) in his mapping. Since these first line supervisors represent a small share of the number of workers and wage bill for SOC 41 we assign this SOC code to routine occupations (r).

[21] The BLS OES data set does not cover agriculture sectors and therefore the occupational disaggregation in SAGE's agricultural and forestry sector is based solely on the forestry sectors included in the OES data set.

39	Personal Care and Service Occupations	m
41	Sales and Related Occupations	r
43	Office and Administrative Support Occupations	r
45	Farming, Fishing, and Forestry Occupations	r
47	Construction and Extraction Occupations	r
49	Installation, Maintenance, and Repair Occupations	r
51	Production Occupations	r
53	Transportation and Material Moving Occupations	r

As shown by Autor et al. (2003) and Acemoglu and Autor (2011), tasks performed as part of routine occupations are the ones most subject to machine displacement. Therefore, in production we model capital as a substitute for routine occupations, and more particularly the tasks they perform, in a constant elasticity of substitution (CES) function. The routine labor and capital composite then enters a CES nest with tasks performed by non-routine occupations. This structure is presented in Figure 5.

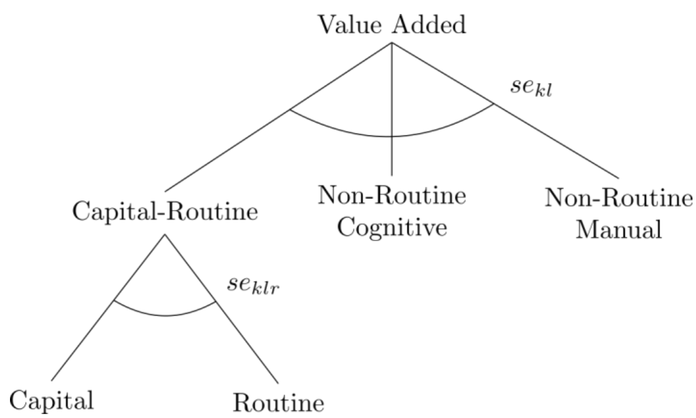

Figure 5: Updated Value-Added Nest with Heterogeneous Labor

The labor demand structure used in this paper is similar to Carrico and Tsigas (2014) when disaggregating U.S. labor market demands by occupation. We develop a novel estimation framework to parameterize the adjusted elasticity structure. Carrico and Tsigas (2014) maintain the CGE model's default value-added substitution elasticities for se_klr and select an arbitrarily small value of se_kl. In doing so, they implicitly assume that the overall elasticity governing the substitution between capital and aggregate labor is different from the original estimate of se_kl used in the model. Their results are therefore influenced by two changes: the addition of occupational heterogeneity and the implicit adjustments to the aggregate capital-labor substitution elasticity at the sectoral level. If the original sectoral capital-labor substitution elasticities are well grounded in empirical observations of substitution across the aggregate labor and capital inputs for the sector, one would want the new production structure to maintain consistency with those values. Therefore, we approach the calibration of the new production structure in a way that ensures the sector's aggregate capital-labor substitution elasticities remain equal to the original estimates included in the default specification of SAGE. To make this feasible, we assume a value for the top-level substitution elasticity, se_kl, in the updated value-added nest with heterogeneous labor and solve for the value of se_klr that maintains the original estimate of the aggregate capital-labor substitution elasticity for the sector.

Let *i* denote a subscript for unit of observation. We estimate sector-specific adjusted elasticities using random draws from a uniform distribution of prices around the reference equilibrium. As in the calibration of the SAGE baseline, we assume that reference prices in the base period are unity. Let $\overline{lr}_{rs}$, $\overline{lc}_{rs}$, and $\overline{lm}_{rs}$ be reference levels of labor demands for routine, non-routine cognitive and non-routine manual occupations, respectively. Aggregate labor demands are then defined as $\bar{l}_{rs} = \overline{lr}_{rs} + \overline{lc}_{rs} + \overline{lm}_{rs}$. We characterize random price perturbations as equivalent across labor types. Letting ϵ_i equal the small change from the reference point, we define $\widetilde{pl}_{rsi} = \widetilde{plr}_{rsi} = \widetilde{plc}_{rsi} = \widetilde{plm}_{rsi} = 1 + \epsilon_i$ as the random price draws for each labor type (aggregate, routine, non-routine cognitive and non-routine manual, respectively). Given this assumed price change, the value-added unit cost of the original SAGE cost function is

$$\widetilde{cost}_{rsi} = \left(\theta_{rs}^{k} + \left(1 - \theta_{rs}^{k}\right) \widetilde{pl}_{rsi}^{1-se_{kl_s}}\right)^{\frac{1}{1-se_{kl_s}}} \tag{1}$$

where θ_{rs}^{k} denotes the value share for capital demands. The price of capital is fixed to one in the estimation framework as we isolate changes in aggregate labor demands consistent with small changes in the price of labor. Using Shepard's Lemma, the equilibrium level of aggregate labor demands at the new wage rate is

$$\tilde{l}_{rsi} = \bar{l}_{rs} \left(\widetilde{cost}_{rsi} \big/ \widetilde{pl}_{rsi}\right)^{se_{kl_s}} \tag{2}$$

Given this distribution of aggregate labor demands, we estimate the values of se_{klr_s} minimizing the deviation in the overall change to sectoral labor demand between the original and adjusted labor demand structure. The unit cost function associated with the adjusted labor demand structure is written as

$$C_{rsi} = \left(\theta_{rs}^{kr} PKR_{ri}^{1-se_{kl_s}} + \theta_{rs}^{m} \widetilde{plm}_{rsi}^{1-se_{kl_s}} + \theta_{rs}^{c} \widetilde{plc}_{rsi}^{1-se_{kl_s}} \right)^{\frac{1}{1-se_{kl_s}}} \quad (3)$$

where θ_{rs}^{kr}, θ_{rs}^{m}, and θ_{rs}^{c} denote value shares for the capital-routine labor composite, non-routine manual labor, and non-routine cognitive labor demands in the reference data. PKR_{rsi} denotes the composite price between capital and routine labor, with θ_{rs}^{r} being the value share for routine labor demand.

$$PKR_{rsi} = \left(\theta_{rs}^{k} + \theta_{rs}^{r} \widetilde{plr}_{rsi}^{\,1-se_{klr_s}} \right)^{\frac{1}{1-se_{klr_s}}} \quad (4)$$

Using Shepard's Lemma, we can characterize the input demand functions as

$$L_{rsi}^{m} = \overline{lm}_{rs} \, {\partial C_{rsi}}/{\partial \widetilde{plm}_{rsi}} \quad (5)$$

$$L_{rsi}^{c} = \overline{lc}_{rs} \, {\partial C_{rsi}}/{\partial \widetilde{plc}_{rsi}} \quad (6)$$

$$L_{rsi}^{r} = \overline{lr}_{rs} \, {\partial C_{rsi}}/{\partial \widetilde{plr}_{rsi}} \quad (7)$$

Aggregate labor demand can therefore be denoted as, $L_{rsi} = L_{rsi}^{m} + L_{rsi}^{c} + L_{rsi}^{r}$. We estimate the values of se_{klr_s} using a least squares penalty function that minimizes the weighted percent deviation between L_{rsi} and $\tilde{l}_{rsi}$:

$$\min \textstyle\sum_{rsi} \tilde{l}_{rsi} \left({L_{rsi}}/{\tilde{l}_{rsi}} - 1 \right)^2 \quad (8)$$

Since the estimate of se_{klr_s} is conditional on the assumed value of se_{kl_s}, we consider a range of 0%, 20%, and 100% of the reference capital-labor substitution elasticities. The first two sets of values assume a a reatively small value for se_{kl_s} limiting substitution possibilities between non-routine tasks and the routine-capital, suggesting that tasks performed by non-routine occupations are strong gross price complements to both capital and tasks performed by routine occupations. The third set of values is reported as a sensitivity to verify the robustness of the framework. If the assumed value of se_{kl_s} is equal to the original value, then the calibrated value of se_{klr_s} should equal se_{kl_s} as the adjusted elasticity is transformed into the original framework. Table 5 reports the adjusted elasticities as compared to the original set of values used in the SAGE model.

Table 5: Estimated Capital-Routine Labor Substitution Elasticities (se_{klr_s})

Sector	Assumed level of se_kl			Original se_kl
	0%	20%	100%	

agf	1.171	1.151	1.070	1.070
cru	1.370	1.255	0.790	0.790
col	0.908	0.885	0.790	0.790
min	0.908	0.885	0.790	0.790
ele	1.438	1.351	1.002	1.002
gas	1.199	1.118	0.790	0.790
wsu	1.106	1.085	1.002	1.002
con	0.188	0.185	0.170	0.170
fbm	0.244	0.239	0.220	0.220
wpm	0.130	0.128	0.120	0.120
ref	1.134	1.054	0.732	0.732
chm	0.395	0.364	0.240	0.240
prm	0.133	0.130	0.120	0.120
cem	0.213	0.210	0.200	0.200
pmm	0.201	0.197	0.180	0.180
fmm	0.199	0.195	0.180	0.180
cpu	0.188	0.171	0.100	0.100
tem	0.229	0.219	0.180	0.180
bom	0.418	0.406	0.360	0.360
trn	0.562	0.558	0.541	0.541
ttn	0.145	0.144	0.140	0.140
srv	0.539	0.493	0.308	0.308
hlt	1.260	1.125	0.580	0.580

As expected, the estimated levels of se_{klr_s} increase as the assumed levels of se_{kl_s} decrease. The magnitude of the increase is dependent on structural assumptions in the model as well as underlying data on value shares. When we assume that se_{kl_s} in the adjusted labor demand structure is equivalent to the original labor demand structure value, the estimated value of $se_{klr_s} = se_{kl_s}$ which confirms that the estimation framework is operating correctly. We use the 0% values as the default in our model and consider the 20% values as a sensitivity.

3.2.2 Labor Supply Specification

The Census Bureau's Current Population Survey (CPS) March Supplement for the benchmark year is used to disaggregate household labor supply in SAGE. [22] The Census occupational codes are mapped to the major SOC codes and then wage earnings by occupation are aggregated to the SAGE regions and representative households using the person level weights. The aggregate regional wage payments to a

[22] For the 2016 benchmark year we use the 2017 CPS March Supplement as that survey asks respondents about the year 2016.

given occupation derived in the previous step are distributed to the region's representative households based on their share of regional earnings for that occupation as reported in the CPS. This can lead to a small imbalance in the social accounting matrix (SAM) aggregate earnings for a representative household, since they are not constrained to be equal to the previous value. Therefore, the SAM is rebalanced using the routine described in Marten and Garbaccio (2018). The disaggregated labor supply shares are presented in Figure 6. The shares are plotted at the national level, but the pattern is consistent across the regions in the model. A large share of labor earnings for low-income households is generated by time spent in non-routine manual occupations, and this share decreases with income to a small share for high-income households. The opposite holds for labor earnings from time spent in non-routine cognitive occupations, which is a small share of total earnings for low-income households, but increases with income and is the majority source of labor income for high income households.

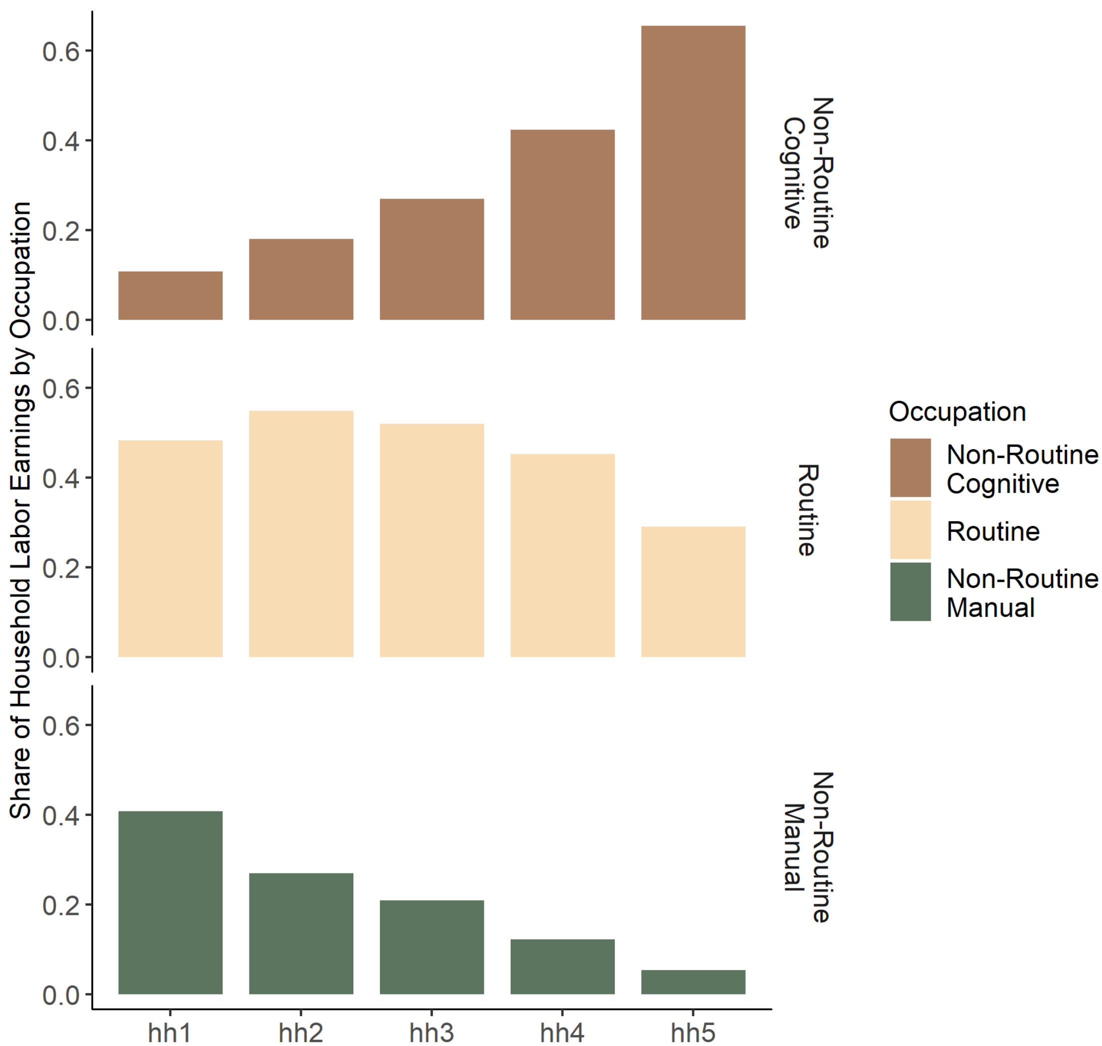

Figure 6: Household Labor Earnings by Occupation

To capture occupational mobility, representative households are endowed with a given set of occupational skills as represented in the benchmark labor supply. We model household labor supply across occupations using a Constant Ratio of Elasticity of Transformation, Homothetic (CRETH) function (Figure 7). In the benchmark equilibrium it is assumed that labor is optimally supplied to each occupation conditional on the set of relative prices. In response to changes in relative wages households can shift labor across occupations. Hhowever, labor being shifted from occupation i to occupation j is not as effective in the destination occupation as labor that is originally employed in occupation j.

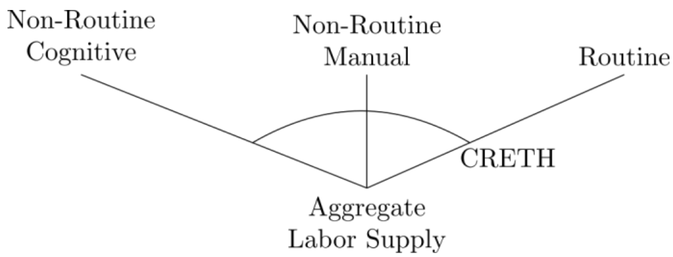

Figure 7: Household Labor Transformation

The CRETH function, as introduced by Vincent et al. (1980), is an extension of the Constant Ratio of Elasticity of Substitution, Homothetic (CRESH) function defined by Hanoch (1971) that has been adapted to the transformation space. The CRETH function is implicitly defined as:

$$F(l_{trh}, ls_{trh1}, \dots, ls_{trhn}) = \sum_{o=1}^{n} a_{rho} \left[\frac{ls_{trho}}{h(l_{trh})}\right]^{b_{rho}} - 1 = 0 \qquad (9)$$

for aggregate labor supply level l_{trh} being transformed into *n* occupations denoted ls_{trho}, where $a_{rho} > 0$ and $b_{rho} > 1$ to ensure that the function is globally strictly quasi-convex. Under constant returns to scale $h(l_{trh}) = l_{trh}$, such that the implicit definition of the function in (9) reduces to:

$$\sum_{o=1}^{n} a_{rho} \left[\frac{ls_{trho}}{l_{trh}}\right]^{b_{rho}} - 1 = 0 \qquad (10)$$

The Allen-Uzawa transformation elasticities are:

$$\sigma_{ij}^{a} = \frac{\left(\frac{1}{1-b_{rhi}}\right)\left(\frac{1}{1-b_{rhj}}\right)}{\sum_{k=1}^{n}\theta_k\frac{1}{1-b_{rhk}}}, i \neq j \tag{11}$$

and

$$\sigma_{ii}^{a} = \frac{\left(\frac{1}{1-b_{rhi}}\right)^2}{\sum_{k=1}^{n}\theta_k\frac{1}{1-b_{rhk}}} - \frac{1}{\theta_i(1-b_{rhi})} \tag{12}$$

where θ_o is the earnings share:

$$\theta_o = \frac{p_{tro}ls_{trho}}{\sum_{j=1}^{n}p_{trj}ls_{trhj}} \tag{13}$$

Since the CRETH function is homothetic, θ_o and therefore equation (11) will be independent of l_{trh} and hence the constant ratio of elasticity of transformation property holds. Solving the Lagrangian for the earnings maximization problem yields an implicit definition of the optimal labor supply to occupation o, such that:

$$ls_{trho} = \left(\frac{p_{tro}(l_{trh})^{b_{rho}}}{a_{rho}b_{rho}}\left[\sum_{j=1}^{n}\frac{p_{trj}ls_{trhj}}{b_{rhj}}\right]^{-1}\right)^{\frac{1}{b_{rho}-1}} \tag{14}$$

The CRETH coefficients a_{rho} are calibrated to ensure that the production function replicates the benchmark. In the benchmark, prices $\overline{p}_{ro}$ are normalized to unity, where ¯ represents a benchmark value. For (14) to hold for the benchmark values, we require:

$$a_{rho} = \frac{\overline{ls}_{rho}}{b_{rho}}\left(\sum_{j=1}^{n}\frac{\overline{ls}_{rho}}{b_{rho}}\right)^{-1}\left(\frac{\overline{ls}_{rho}}{\overline{l}_{rh}}\right)^{-b_{rho}} \tag{15}$$

The transformation elasticities are defined by b_{rho} and are not affected by the calibration of a_{rho}.

The CRETH exponents b_{rho}, which define the transformation elasticities across occupations, are calibrated to match empirical estimates of the cost of switching occupations. Specifically, we calibrate to the wage changes estimated by Cortes (2016) in Table 6.[23] Consider a worker switching from occupation *i* to occupation *j*. The estimates in Table 6 define the target value for a switcher's wage in the destination occupation relative to the average wage in the destination occupation. We denote this value as β_{ij}.

Table 6: Wage of Switcher Relative to Average Destination Wage

[23] The estimates are based on the occupation spell fixed effect estimates in Cortes (2016) Table A.4. Cortes (2016) does not report results for workers switching into routine occupations. We estimated those values using the same data and methodology as Cortes (2016).

		Destination		
		Non-Routine Cognitive	Non-Routine Manual	Routine
Origin	Non-Routine Cognitive		0.873	1.140
	Non-Routine Manual	0.395		0.663
	Routine	0.641	0.640	

There are several observations worth noting. First, individuals who move from a non-routine manual to a non-routine cognitive occupation, on average, earn 60% less than workers already employed in a non-routine cognitive occupation. This reflects the fact that workers switching from non-routine manual occupations (while likely on the upper end of skill distribution amongst manual workers) are less skilled in the tasks demanded of them in a non-routine cognitive occupation than the average worker in that occupation. Second, routine workers who switch into non-routine cognitive or non-routine manual occupations also experience a cost, but it is less severe: they earn, on average, 36% less than workers previously employed in those occupations. This is also the case for non-routine manual workers who move to a routine occupation. Finally, workers in non-routine cognitive occupations that switch to a non-routine manual or a routine occupation, earn a wage within 15% of the average wage for those occupations, suggesting greater mobility for those workers. If they switch to a routine occupation, they actually earn slightly more on average, likely because they can select into the most highly paid routine jobs available given their skill set.

Assume that household *h* in region *r* shifts a share, α, of its labor supply from occupation *i* to occupation *j*. Labor supply to all other occupations remains constant at benchmark levels. The effective labor supply to occupation *i* is now $(1-\alpha)ls_{0rhi}$ and non-affected occupations have labor supply that remains at the benchmark levels, $ls_{0rhk}\ \forall k \neq i, j$. Effective labor supply for occupation *j* is determined by (10). Given that prices are normalized to unity in the benchmark, the goal is for the new effective labor supply to occupation *j* to equal $ls_{0rhj} + \beta_{ij}\alpha ls_{0rhi}$. There are more calibration targets than parameters in the CRETH function, so we calibrate $b_{rho}\ \forall\ o$ by minimizing the squared percent deviation for each calibration target. More specifically, if the effective labor supply in occupation *j* that satisfies (10) is denoted as ls'_{0rhj}, than the objective function is:

$$\min \sum_i \sum_{j \neq i} \left(\frac{ls'_{0rhj}}{ls_{0rhj} + \alpha \beta_{ij} ls_{0rhi}} - 1 \right)^2 \tag{16}$$

To calibrate b_{rho} we set α to 0.01 to represent a marginal change.

Given the disaggregated benchmark labor supply data in SAGE and the target relative wage rates of switchers in Table 6, the calibrated relative wage rates by household and region are presented in Figure 8. In other words, Figure 8 presents the implicit value of β_{ij} based on the calibrated version of the CRETH function conditional on the region and representative household of the switcher. The horizontal lines represent the target values and the circles represent the calibrated values, where the size of the circle represents the share of a household's income from time spent in the origin occupation. Ideally, the larger circles will be relatively close to the target, which is the case in most instances.

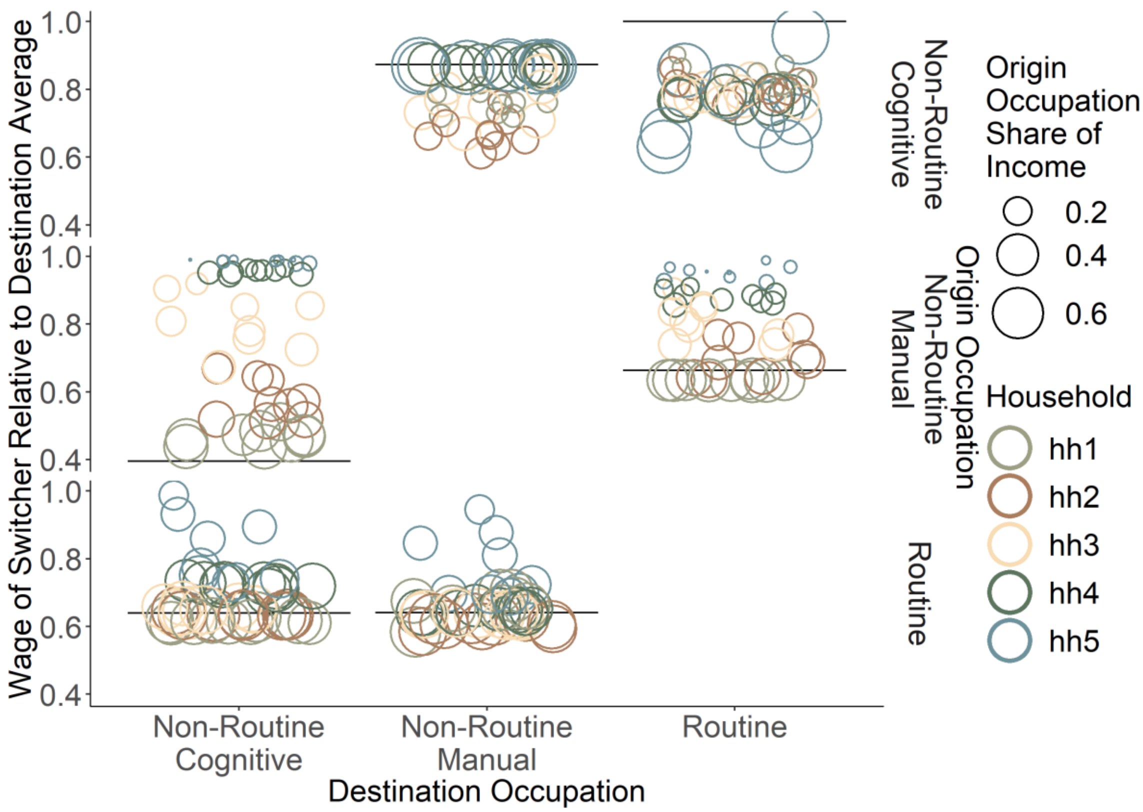

Figure 8: Calibrated Cost of Switching Occupations

A limitation of our calibration approach is that the lack of explicit heterogeneity within occupations. Some of this heterogeneity is implicitly captured by the calibration to empirical estimates derived from a model of worker heterogeneity. However, by focusing on representative workers in our framework we cannot represent some of the nuances observed in the empirical estimates such as the difference in wage effects for movers versus stayers (e.g., Cortes (2016) finds that non-routine cognitive workers switching to routine occupations earn, on average, more than the workers staying in routine occupations). We need to limit that calibration target to one, which is itself a difficult calibration target even with the flexibility of the CRETH function. As can be seen in Figure 8, reflecting a costless transition, in terms of relative wages, for only one occupation pair presents a challenge. Another possible limitation of our calibration to Cortes (2016) is that the underlying data reflect both voluntary and involuntary job switches. To the extent that we think regulation mainly induces one type over another, use of the average loss in wages when transitioning across occupations may be biased upward (in the case of mainly involuntary) or downward (in the case of mainly voluntary). This may tie directly to how far in advance a regulatory requirement is announced.

3.3 Modeling Regulations

While there are some notable exceptions, U.S. regulations rarely rely on market-based incentives. For example, in the environmental and energy setting, it is common for regulations to resemble an emissions rate standard, specify the use of certain types of pollution control equipment, and/or require the alteration of production processes. In the case of labor safety regulations, standards often set workplace practices or require personal protective equipment for workers engaged in particular practices. While modifying input use to reduce a negative externality is often incentivized by regulation, the output channel does not aid facilities in meeting regulatory requirements in these instances. Thus, regulatory requirements can often be interpreted as technology mandates for a sector to use more inputs to produce the same amount of output. We follow Marten et al. (2018) and focus our analysis on the additional inputs to production required for compliance.

To capture regulation in the model, we explicitly specify the input requirements for regulatory compliance. For the standard manufacturing and services production functions, production now requires both the traditional production activity and a compliance activity, which is itself a Leontief function of inputs used in regulatory compliance. Figure 9 presents the updated production function inclusive of the compliance activity. For a typical regulation where the per unit compliance costs do not change with the level of output, specifying the top-level nest as Leontief is a reasonable starting point. There is less information available on whether a Leontief representation is a sensible depiction of how inputs into compliance activities respond to relative price changes. However, since regulatory compliance is not a well-defined activity within the national accounts, and there is a dearth of available information in the literature, we do not attempt to specify unique substitution elasticities across compliance inputs. To understand whether results are sensitive to how regulation is introduced into the model, Section 5 instead represents the additional inputs required to comply as productivity shocks in the regulated industry (e.g., Hazilla and Kopp, 1990; Pizer and Kopp, 2005; Pizer et al., 2006). One potential pitfall of this approach is that the substitution possibilities across inputs to compliance activities are the same as across inputs to production activities in the regulated sector.

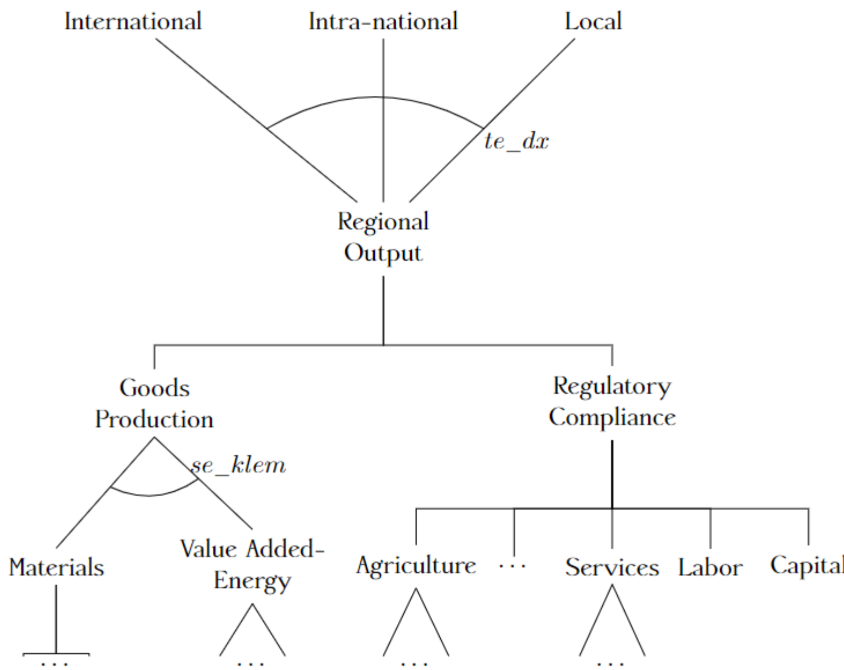

Figure 9: Incorporation of Explicit Compliance Requirements

To focus our analysis, we study the case of environmental regulations affecting the manufacturing sector. A substantial share of environmental regulations requires abatement activities in manufacturing sectors for compliance. In addition, the labor literature in Section 2 identifies stagnation in routine occupations, often associated with manufacturing, as one of the primary drivers of wage polarization.

The magnitude of the shock is calibrated to estimated direct compliance costs of the 1990 Clean Air Act Amendment requirements in manufacturing in 2020 (U.S. EPA, 2011). These estimates are prospective and based primarily on regulations promulgated through September 2005. They do not reflect subsequent regulatory actions, major changes in implementation, or requirements that were vacated by the courts (e.g., CAIR). However, they provide a reasonable illustrative approach to calibrate the magnitude and sectoral and regional distribution of regulatory costs in our scenarios. Table 6 shows how these direct compliance cost estimates map to the manufacturing sectors in SAGE. These costs are assumed to scale with output in future years. Moreover, for the sake of simplicity, we assume that all engineering costs are *net* of tax payments and transfers. Chemical manufacturing and balance of manufacturing bear 67% of manufacturing compliance costs, following by wood and paper product manufacturing (10%), and transportation equipment manufacturing (9%).[24] As a whole, manufacturing was expected to bear about 25% of the total cost of complying with the Clean Air Act Amendments.

Table 7: Estimates of Direct Compliance Costs for Clean Air Act in 2020

SAGE Sector	Description	Billion 2016$	Share of Manufacturing Costs	Share of Total Costs
Manufacturing				
bom	Balance of manufacturing	4.6	38%	10%
cem	Cement, concrete, & lime	0.2	1%	0%
cpu	Electronics and technology	0.1	1%	0%
chm	Chemical manufacturing	3.5	29%	8%
fbm	Food & beverage manufacturing	0.1	1%	0%
fmm	Fabricated metal product manufacturing	0.6	5%	1%
pmm	Primary metal manufacturing	0.7	5%	1%
prm	Plastics & rubber products	0.1	1%	0%
tem	Transportation equipment	1.1	9%	2%
wpm	Wood & paper product manufacturing	1.2	10%	3%
Energy				
col	Coal mining	0.2		0%
cru	Crude oil extraction	0.3		1%
ele	Electric power	17.6		39%
gas	Natural gas extraction & distribution	0.9		2%
ref	Petroleum refineries	1.2		3%
Other				
con	Construction	1.9		4%
agf	Agriculture, forestry, fishing & hunting	0.2		1%
hlt	Healthcare services	0.0		0%
min	Metal ore & nonmetallic mineral mining	0.2		0%
srv	Services	2.4		5%
trn	Transportation	0.8		2%
ttn	Truck transportation	7.7		17%
wsu	Water, sewage, & other utilities	0		0%
	Total	45.5		100%

Note: These estimates are based on aggregating the direct compliance cost estimates in Table J-2 of U.S. EPA (2011) to the national SAGE sectors.

[24] The two main subsectors that make up the majority of the compliance costs in balance of manufacturing are other non-metallic minerals manufacturing and miscellaneous manufacturing (US EPA 2011).

Figure 10 reports the distribution of costs by Census Division. The Middle Atlantic Division (New York, Pennsylvania, and New Jersey) bear the largest proportion of the direct compliance costs (22%) followed by the Pacific (inclusive of Alaska and Hawaii; 18%), East North Central (17%), West South Central (17%), and South Atlantic (13%) Census Divisions. The remaining Census Divisions individually bear less than 5% of the total direct compliance costs in manufacturing. Assuming the engineering costs in Table 6 grow at the baseline rate of output for the regulated manufacturing sectors, the annualized engineering costs are estimated at $20.6 billion in 2016 dollars.[25]

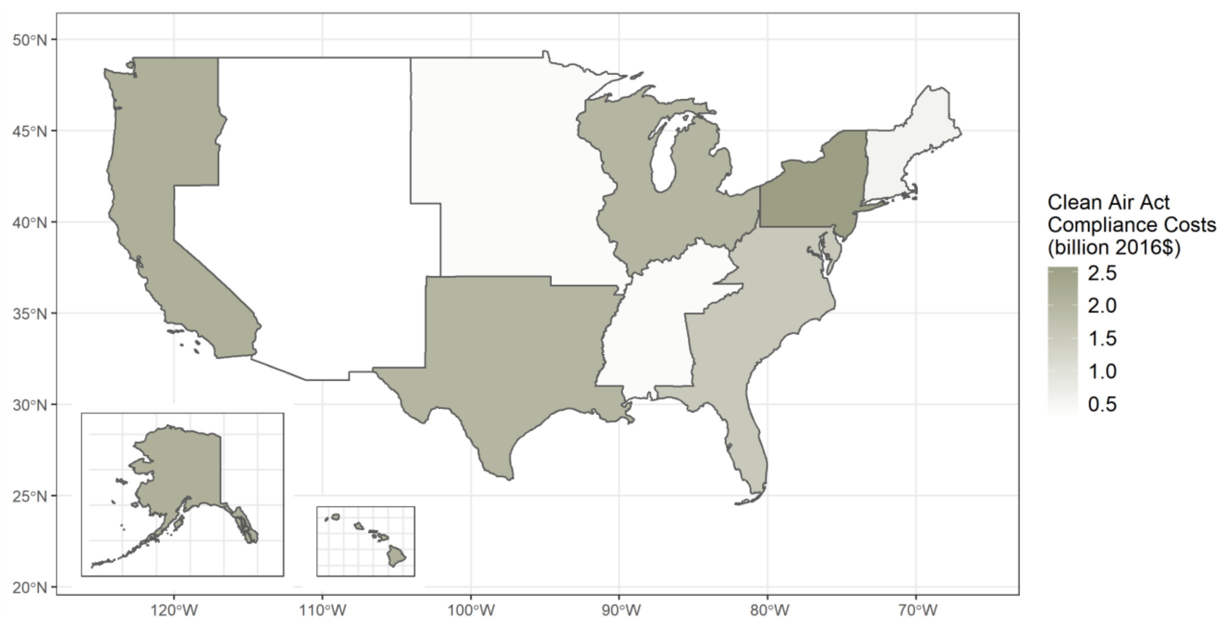

Figure 10: Regional Distribution of Direct Compliance Costs in Manufacturing Sectors

We consider a range of bounding cases for the potential input requirements for compliance activities. Specifically, we consider a capital-only and two labor-only cases, one in which compliance is met entirely with non-routine cognitive labor and one in which compliance is met entirely with routine labor.[26] In reality, individual regulations vary widely in their capital- and labor-intensity. For example, among Maximum Achievable Control Technology (MACT) standards (included in the prospective cost estimates for the 1990 Clean Air Act Amendments), capital costs make up 0 percent of the total for the large appliance surface coating rule, about 20 percent for the stationary source reciprocating internal combustion engines (RICE) rule, and 50 percent for the light-duty vehicle MACT rule. In addition, based

[25] This assumes compliance requirements continue into perpetuity with a steady state discount rate of 4.5%.
[26] For manufacturing sectors assumed to comply with the environmental regulatory shock in this paper, less than 1% of reference labor demands in the model are attributed to non-routine manual occupations.

on a cursory review of regulatory analyses for several economically significant rulemakings, we find that it is not uncommon for EPA to assume that compliance activities such as monitoring, testing, certification, recordkeeping, and the design and installation of end-of-pipe controls require environmental engineers and managers, both of which fall into the non-routine cognitive labor category.[27]

The social cost of regulation is measured using equivalent variation (i.e., the maximum amount of money a representative agent is willing to pay to forego the burden of the regulation). We compute this household-specific value numerically as the difference between the present value of baseline expenditures and those associated with the optimal path of consumption and leisure that would lead to the same level of inter-temporal welfare as the regulatory case but with prices fixed at their baseline values.

4 Results

To examine the impact of occupational affiliation on the social costs of regulation and the distribution of those costs, we compare simulation results with a homogenous labor category to those that incorporate occupational heterogeneity. The homogeneous simulations use the default version of the SAGE model with a single labor category as is common in CGE models. The occupational heterogeneity simulations are based on the labor demand and supply structures detailed in Section 3.2. For our case study of environmental regulations in the manufacturing sector, Table 8 presents the annualized equivalent variation aggregated across all representative households. The social costs are presented for both labor representations (i.e., homogenous and heterogeneous) and the three bounding cases for the compliance input requirements (i.e., capital-only, non-routine cognitive labor only, and routine labor only). In the homogenous labor case, by assumption, there is no distinction between using non-routine cognitive labor and routine labor for regulatory compliance.[28] Therefore, they have the same value for the social cost. The general magnitude of the social cost estimates in Table 8 are approximately 7-35% higher than the engineering cost estimate of $20.6 billion. This is roughly consistent with the general equilibrium effects found in Marten et al. (2018).

[27] We looked at the regulatory impact analyses for the 2014 rule on disposal of coal combustion residues from electric utilities, the 2011 mercury and air toxics standards, the 2015 steam electric power generating effluent guidelines, the 2015 Clean Power Plan, and the 2016 formaldhyde emission standards for composite wood products.
[28] A positive equivalent variation here is interpreted as a cost. E.g., the larger the level of EV for a given household, the larger the household would be willing to pay to avoid the regulatory burden. Annualized equivalent variation is calculated assuming an infinite time horizon.

Table 8: Annualized Equivalent Variation [Billion 2016$]

<table>
<tr><th rowspan="2">Compliance Input Requirement</th><th colspan="2">Occupation Assumption</th></tr>
<tr><th>Homogeneous</th><th>Heterogeneous</th></tr>
<tr><td>Capital</td><td>27.3</td><td>27.7</td></tr>
<tr><td>Non-Routine Cognitive Labor</td><td rowspan="2">22.9</td><td>23.5</td></tr>
<tr><td>Routine Labor</td><td>22.0</td></tr>
</table>

The introduction of occupational heterogeneity has a relatively small effect on aggregate social costs, ranging from a -4% to 3% difference relative to the social costs estimated under the case of homogenous labor.[29] While occupational heterogeneity has a minimal impact on estimates of the aggregate social cost, it can have a notable impact on the incidence of those costs. Independent of the inputs required for compliance activities, the increased production costs due to the regulation result in a contraction in the regulated sectors' output. However, some occupations employed in the sector may not experience a decrease in employment along with the contraction in output. Figure 11 presents the total percent change in labor demand in the regulated sectors along with a decomposition based on changes in labor demand for production activities and compliance activities.[30] The rows represent the three different compliance input scenarios (capital only, non-routine cognitive labor only, and routine labor only). The columns provide the decomposition in aggregate labor demand across production and compliance activities.

[29] We also investigate the social cost implications of scaling the policy shock (e.g., compliance costs) to be 10% and 150% of its original size. Like Marten et al. (2019), we find that the difference between social costs and engineering costs declines with the size of the policy shock. We do not observe any significant deviations between the default version of SAGE and the updated model with occupational heterogeneity in this result.

[30] Because compliance activities are zero in the baseline, labor demand changes due to regulatory compliance are calculated as the percent of baseline labor demand by occupation whereas production and total changes are calculated as a percentage change from baseline levels.

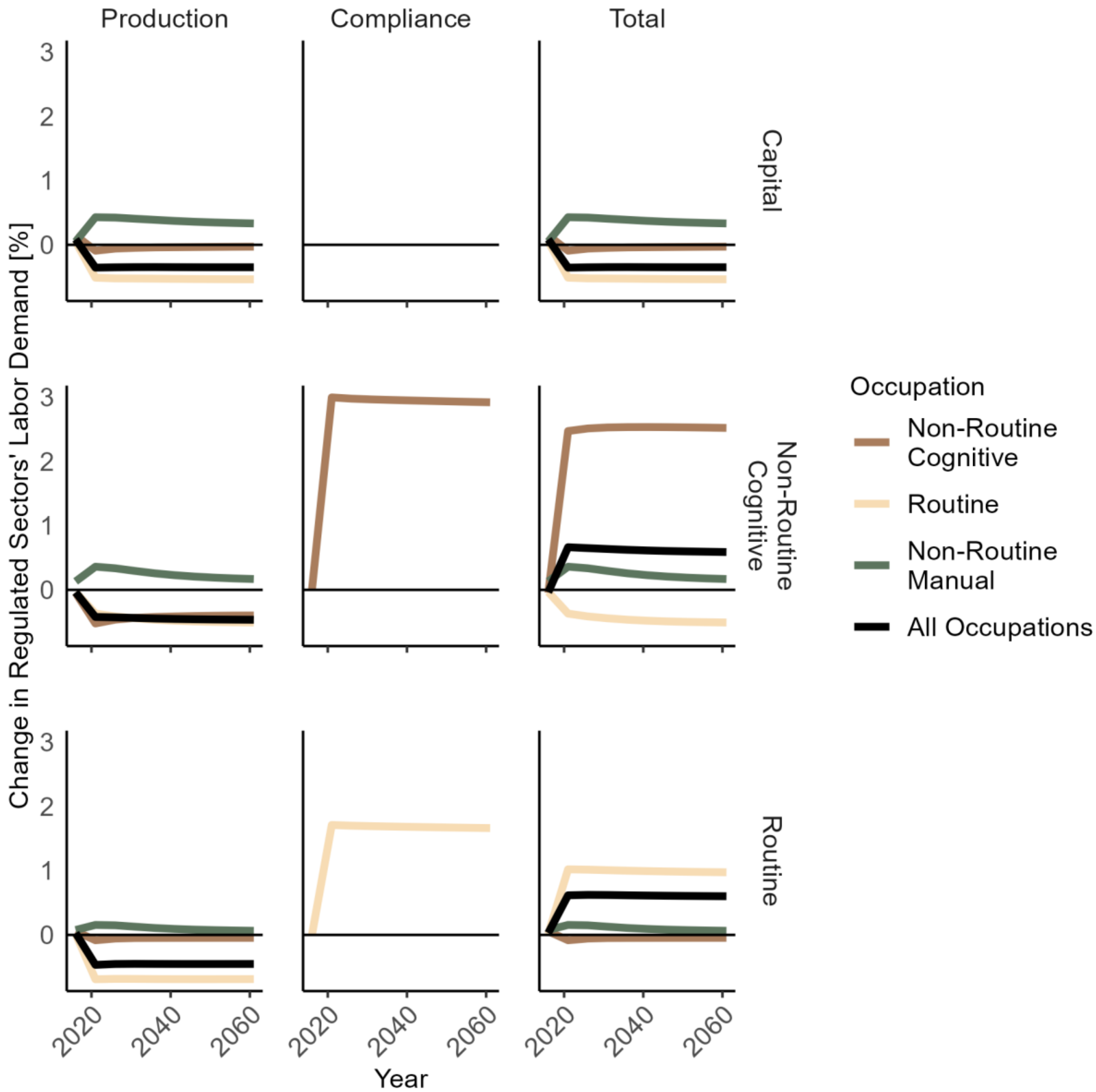

Figure 11: Change in Regulated Sectors' Labor Demand by Activity and Occupation

There are four key effects that determine the overall change in labor demand for an occupation in the regulated sectors. First, the contraction in the regulated sectors' output places downward pressure on the demand for all labor. Second, as relative prices for routine labor and capital change, there is substitution between them. When the compliance activity is capital intensive the additional demand for capital in the regulated sectors places upward pressure on the rental rate for capital, which cause firms to substitute away from capital towards routine labor in production activities. When the compliance activity predominately requires routine labor, the opposite occurs. The increased demand for routine labor for compliance activities places upward pressure on the wage rate for routine occupations causing firms to shift away from routine labor towards capital in production activities. Third, the substitution possibilities between non-routine manual labor, non-routine cognitive labor, and the capital-routine labor composite is modeled as Leontief in production activities meaning that any reduction or increase in labor demand due to wage changes is matched across these categories (the sensitivity to this assumption is tested below). Finally, the equilibrium changes in occupation-specific labor markets (and in turn demand in the regulated sectors via the price signal) are dependent on the degree of flexibility in the labor supply functions. These four effects will differ across occupations, leading to notably different changes in demand for their services in the regulated sectors.

The estimates in Figure 11 highlight that employment in the regulated sectors, especially for particular occupations, could increase as the result of regulation.[31] When the regulatory compliance activities are labor intensive, changes in total labor demand in the regulated sectors is dominated by the those compliance activity demands.[32] Aggregate labor impacts in the regulated sectors are similar across both scenarios where the compliance requirements are labor intensive shocks.[33] In the scenario where compliance requirements are capital intensive, the increased capital demand for compliance puts upward pressure on the rental rate for both the regulated and unregulated sectors. Because regulated sectors are concentrated in manufacturing, which is parameterized to have more limited substitution possibilities between capital and routine labor relative to the unregulated sectors (i.e., smaller se_{klr_s}), the demand for routine labor shifts relatively more toward the unregulated sectors than the regulated sectors.

[31] A regulated sector responds to new requirements by reducing output, which then reduces demand for all inputs to production, and by adjusting its input composition. How adjustments to input composition affect employment depends on whether the regulatory activity and labor are substitutes or complements. Berman and Bui (2001) find a small, slightly positive net employment effect in the refinery industry in Los Angeles, California in response to NOx abatement requirements. They posit a similar response in other capital-intensive industries such as cement, chemicals, transportation, and heavy manufacturing, noting that end-of-pipe technologies are often used to abate emissions in existing plants, and that these technologies are likely complements to labor. When requirements are met through process changes Berman and Bui posit that the net employment effect on the regulated sector is likely negative when requirements are instead met via process change due to the installation of more efficient, labor-saving technology.

[32] In the scenario where compliance requirements are predominately non-routine cognitive labor, the percentage change in non-routine cognitive labor for compliance activities is larger than the percentage increase in routine labor for compliance when compliance requirements are predominantly routine labor because the regulated sectors employ more routine labor in the baseline.

[33] The model reports slightly increased aggregate levels in production use of non-routine manual labor for regulated sectors. Non-routine manual makes up less than 1% of total labor demand in the regulated sectors. There are some regulated region-industry pairings that do not use non-routine manual labor and therefore are not associated with a reduction in non-routine manual labor demand from reductions in output (as in the case of routine and non-routine cognitive) leading to a small, but positive aggregate percent change.

Figure 12 presents the percent change in economy-wide demand for different occupations across both regulated and unregulated sectors, where the rows represent the different scenarios for the compliance input requirements. The line-type compares a version of SAGE with the adjusted labor demand and labor supply characterizations ("Heterogeneous: CRETH") with the default SAGE model with a single labor category ("Homogeneous"). In general, the aggregate change in labor across all occupations is similar between the two versions of the model. However, the homogeneous case misses important distinctions across occupations that are important for tracing out the incidence of regulatory costs.

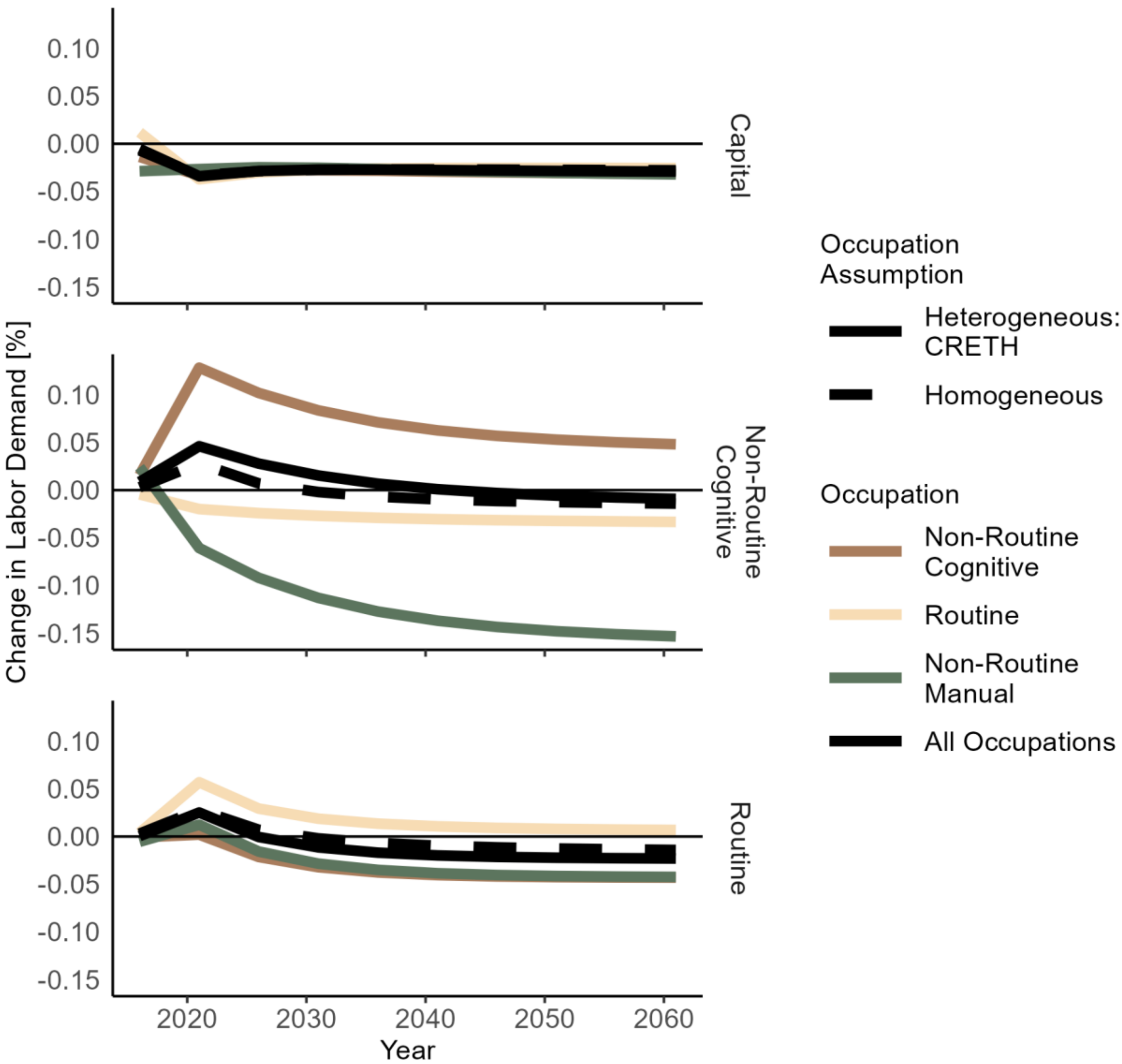

Figure 12: Change in Total Aggregate Labor Demand by Occupation

As previously noted, when compliance activities are capital intensive there will be upward pressure on the capital rental rate, which causes firms to substitute away from capital towards routine labor. This effect is observed in the top panel of Figure 12. A larger share of the overall decrease in production occurs in the regulated sectors, and the manufacturing sectors disproportionately employ routine labor. Absent the substitution effect, we expect that overall demand for routine labor would experience a greater decrease than that of other occupations. However, the substitution effect mutes the impact on the demand for routine labor, such that all occupations exhibit a similar decrease in demand. When the compliance activities in the regulated sectors require predominantly routine labor (bottom panel of Figure 12), then the wage rate for routine occupations increases and the substitution effect with capital works in the opposite direction. In response to the higher wage rate, firms in the unregulated sectors substitute away from routine labor towards capital. As a result, the roughly one percent increase in demand for routine labor in the regulated sectors (Figure 11) is partially offset by a decrease in demand in the unregulated sectors. In the long run, the demand for non-routine occupations is similar to changes that occur in the capital-intensive regulation scenario since the dominant effect for these occupations is the overall contraction in production. Note, however, that general equilibrium composition effects do cause some differences, particularly in the early simulation years.

When compliance requires primarily non-routine cognitive labor, the increased demand for these occupations in the regulated sector places upward pressure on the non-routine cognitive wage rate. However, by definition, firms in the unregulated sectors (as well as the regulated sectors) are unable to substitute away from these occupations towards capital. While there is some ability for firms to substitute towards other intermediate inputs, overall, the opportunities to adapt to changes in the wage rate for non-routine occupations is more limited. Moreover, the ability for households to shift their supply of labor to non-routine cognitive occupations from routine and non-routine manual is also limited. As a result, the increase in non-routine cognitive labor demand in the regulated sector is partially offset by reductions in the unregulated sectors.

The impact on the real wage rate due to the regulation follows the changes in demand for the different occupations. Figure 13 presents the percent change in the real wage rate by occupation and compliance scenario. The figure also shows the percent change in the real wage rate for a composite occupation when the model assumes labor is homogeneous. In the case of a capital-intensive compliance requirement, there is little difference in effects across occupations. While slight, the real wage rate for routine (non-routine) occupations falls less (more) than the change in the composite wage rate when labor is homogenous. This change in the wage differential when the model includes occupational heterogeneity reflects the differences in the substitution possibilities with capital across occupations. Similarly, for the scenarios with labor-intensive compliance requirements, the occupation required for regulatory compliance experiences an increase in its wage rate relative to other occupations. With homogeneous labor, the wage rate represents a weighted average where these differential effects are essentially canceled out as workers compete away potential scarcity rents generated by the regulations.

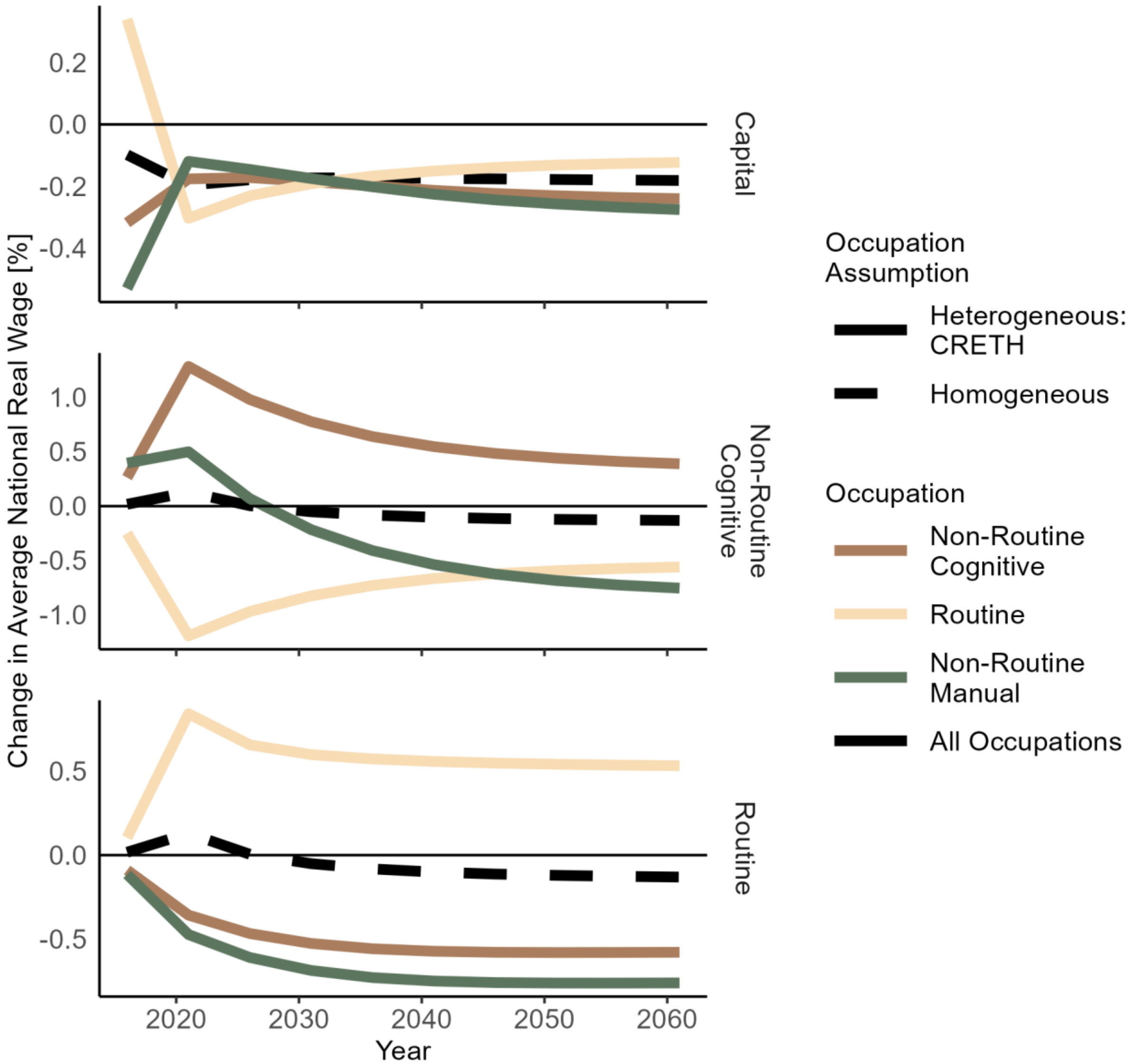

Figure 13: Change in Average National Real Wage by Occupation [%]

In all scenarios, the change in the real wage is greater than the change in the quantity of labor employed. For the labor-intensive compliance scenarios, the change in the real wage is substantially larger than the change in the quantity of labor employed. Because the distribution of these occupations is not uniform across households (Figure 6) the differential effects of regulation on occupational wage rates also will have an impact on the distribution of regulatory costs. Figure 14 presents the annualized equivalent variation by income quintile for the three regulatory scenarios and two representations of labor (i.e., homogenous vs. occupationally heterogeneous). The introduction of occupational heterogeneity has a limited impact on the distribution of costs when the regulation is capital intensive, as would be expected given the relatively small changes in labor demand and wage rates. However, due to the more limited ability to substitute away from capital in response to the higher rental rate, owners bear a greater share of the regulatory costs. This leads to a slightly more progressive distribution of costs than estimated when labor is treated as homogenous.

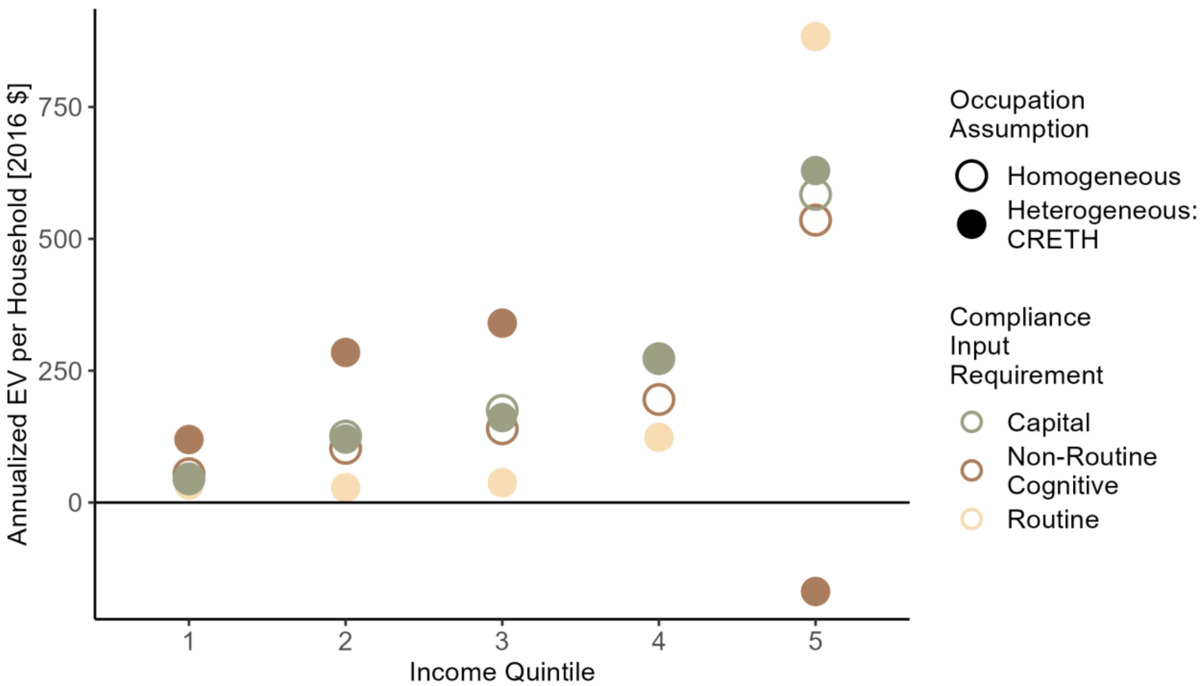

Figure 14: Annualized Equivalent Variation by Income Quintile [Billion 2016$]

The more significant change in incidence occurs when compliance is labor-intensive. Non-routine cognitive occupations are disproportionately filled by members of higher income households, whereas middle income households are primarily reliant on income from routine occupations. As a result, the change in the estimates of incidence follows the change in wage rates when accounting for occupational heterogeneity. In the case where non-routine cognitive occupations are the primary input into compliance activities, higher income households benefit from the increased wage for those jobs whereas middle income households are hurt by the lower wage rate for routine occupations. This would then compound any pre-existing wage stagnation for routine occupations. A similar effect, but in the opposite direction, occurs when the routine occupation is the primary input into compliance activities, leading to higher routine wages and lower non-routine cognitive wages. However, because it is possible to substitute away from routine labor towards capital in response to the regulatory requirements the change in wage rates is muted and so is the change in incidence compared to the case where non-routine cognitive occupations are the primary compliance input.[34]

The impact of occupational heterogeneity on the incidence of regulatory costs also varies regionally. These differences are primarily driven by spatial variation in the burden of the regulatory requirements (see Figure 10). Figure 15 presents the distribution of annualized equivalent variation disaggregated by Census Division. As expected, based on the relative distribution of the compliance requirements, occupational heterogeneity and the role of compliance requirements has the greatest impact in the Middle Atlantic, East North Central, and West South Central regions.[35] In almost every modeled region, if the compliance activity is predominately requires non-routine cognitive labor, accounting for occupational heterogeneity shifts the regulatory burden from the richer households to the lower income households. The opposite is true when the compliance activity is biased toward routine labor.

[34] In Appendix C, we test the sensitivity of our results to the representation of regulatory compliance in the model by modeling the additional inputs required to comply with the environmental regulations as productivity shocks in the regulated industries (e.g., Hazilla and Kopp, 1990; Pizer and Kopp, 2005; Pizer et al., 2006). Modeling compliance as a collection of productivity shocks assumes that the direct costs are calibrated by reducing the productivity of some inputs in the production functions while maintaining fixed levels of output. While similar in interpretation to an explicit compliance requirement as modeled thus far, representing compliance as productivity shocks allow firms to substitute away from the (now) less productive inputs. Generally, we find that our results are largely insensitive to the representation of regulatory compliance. See Appendix C for more information.

[35] Figure 1 provides a mapping of the regions to their names.

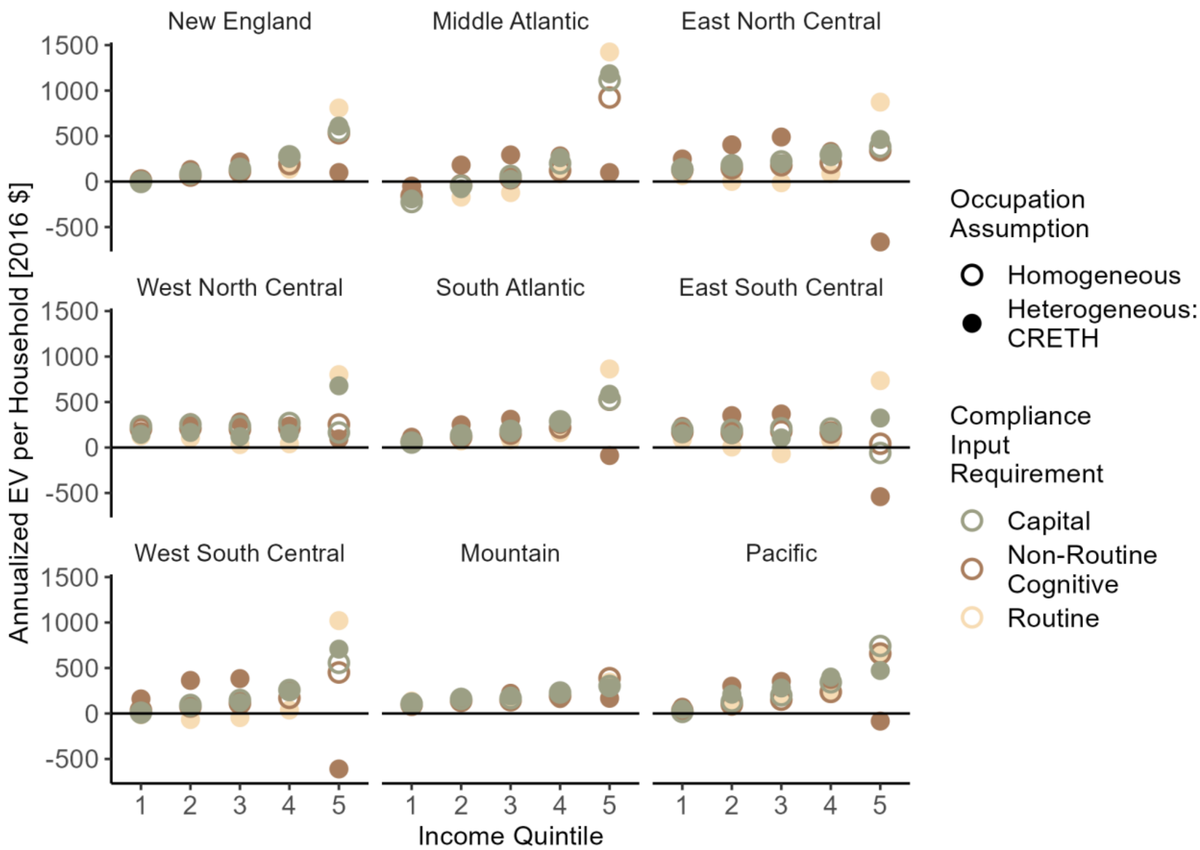

Figure 15: Annualized Equivalent Variation by Income Quintile and Region [Billion 2016$]

4.1 Sensitivity to Labor Supply and Demand Representation

We have introduced occupational heterogeneity into the SAGE model by augmenting the structural relationships between the household supply and sectoral demand for labor relative to the default version of the model. Our main analysis is based on parameterized functions using available evidence from the literature on the asymmetric costs of switching occupations and the substitution possibilities between labor and capital. However, the assumed model structure is not without uncertainty and differs from other existing modeling efforts. For example, our characterization differs from Carrico and Tsigas (2014) who assume a fixed supply of labor by occupation. Therefore, we test the importance of our assumptions and parameterizations of labor supply and demand by comparing the main simulation results to modeled outcomes across several alternatives that vary with regard to occupational flexibility. These comparisons allow us to decouple the relative importance of supply and demand side assumptions on overall social costs and distributional impacts.

We introduce two additional labor supply assumptions to compare with the CRETH function that allow for differentiated costs associated with switching occupations and the bounding case of homogeneous labor, where households can essentially switch between occupations without cost. First, is a case with heterogeneity in occupations but where supply is fixed following Carrico and Tsigas (2014).[36] This can be viewed as a bounding case where it is infinitely costly to switch between occupations. Second, is a constant elasticity of transformation (CET) function. The CET function is a conventional allocation function used in CGE models (e.g., used to operationalize the Armington assumption in SAGE). A single level CET function requires an assumed transformation elasticity that governs the allocation of total labor across occupational categories. We assume a constant elasticity of transformation of 2 that is representative of transition possibilities between a fixed and fully flexible supply of occupations.[37]

Figure 16 reports the difference in total annualized social costs between the main simulation, identified by bolded borders in the figure and two alternative specifications of labor supply. A positive number indicates relatively higher social costs under the alternative specification. The figure is approximately organized from top to bottom as most flexible to least flexible representations of labor supply. Deviations in aggregate social costs from our main simulations range from -6% to 4%. In the scenario where compliance requirements are capital-intensive, reducing barriers to switching occupations allows regulated sectors more opportunity to substitute away from capital, which then mitigates wage impacts, resulting in lower aggregate social costs. When compliance requirements are labor-intensive, differences in social costs are driven by changes in factor incomes and tax interaction effects through reductions or expansions in labor supply. When regulatory compliance requires routine labor, a more flexible labor supply induces a larger shift toward routine labor in response to wage increases, which mitigates the long run wage impact for routine labor as well as the substitution effect toward capital. In general, the more flexible labor supply representations lead to modest reductions in near term investment and longer run consumption.

[36] SAGE models an endogenous labor-leisure choice. Therefore, when we describe labor supply as fixed by occupation, we assume that labor is supplied to each occupation in fixed proportions and scales equivalently to changes in aggregate labor from the labor-leisure choice.

[37] Boeters and Savard (2013) find limited applications of a CET function in representing endogenous transitions between labor categories within CGE models because it does not impose an adding up condition on the total amount of supplied labor. In one instance, Cloutier et al., (2008) model transitions between skilled and unskilled workers in Vietnam using a CET function assuming an elasticity of transformation of 1.5 in their main scenarios and conduct several sensitivity simulations around this parameter given its uncertainty. We acknowledge this feature of the CET function and choose an elasticity value of 2 purely for sensitivity. Most models that ascribe skill-based attributes to representative households assume fixed supplies; this is the main reason why many efforts do not disaggregate skills beyond skilled vs. unskilled workers, as that assumption becomes less plausible with more categories.

When regulatory compliance requires non-routine cognitive labor, the social costs are largely driven more so by labor supply changes and the tax interaction effect. The need for additional non-routine cognitive labor to meet compliance requirements induces a price signal in the form a higher wage for the occupation. Given the limited ability for sectors to substitute away from non-routine cognitive labor in production, the induced wage increase can be relatively large raising compliance costs. When labor supply is modeled as more flexible than the CRETH specification (homogeneous and CET) households are more easily able to respond to the increased wage for the non-routine cognitive occupational category attenuating wage increases, which leads to cheaper compliance options. When labor supply is modeled as fixed (in proportions), meeting the non-routine cognitive labor requirements for compliance requires upward shifts in aggregate labor supply from a larger wage effect relative to the CRETH function, leading to a smaller tax interaction effect which dominates and causes the social cost estimate to decrease.

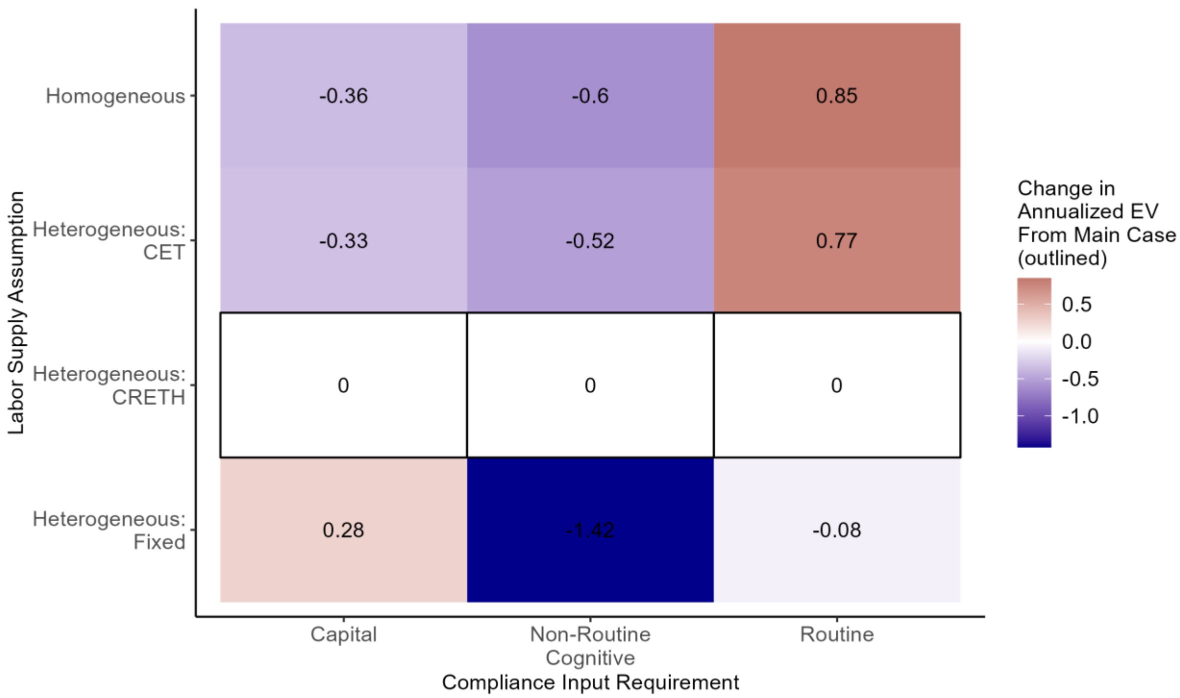

Figure 16: Change in Annualized EV From Main Specification by Alternative Labor Supply Assumptions [Billion 2016$]

We also consider alternative specifications of labor demand. Our main simulation results with heterogeneous occupational categories assume an updated labor demand structure in the value-added sub-nest of the model's production functions (see Figure 5). In that case, the top-level substitution elasticity is zero and the bottom level substitution elasticity between capital and routine labor is calibrated such that the aggregate substitution elasticity between capital and total labor in the production function continues to match the empirical estimates used in the default model. This demand specification is henceforth labeled as “Update (0%)”. We test the sensitivity of our results to this updated structure by considering an alternative labor demand structure that assumes the top-level elasticity is 20% of the reference aggregate capital-labor substitution elasticity, se_{kl_s}, and calibrate bottom level elasticity between capital and routine labor such that aggregate substitution elasticities across capital and all types of labor still matches the empirical estimate se_{kl_s} (see Table 5 for augmented values for se_{klr_s}, labeled as “Update (20%)”). Finally, we also consider the default representation of labor demand where occupations are perfectly substitutable with each other and aggregate substitution elasticity between labor and capital is se_{kl_s} (see Figure 4, labeled as “Default”).

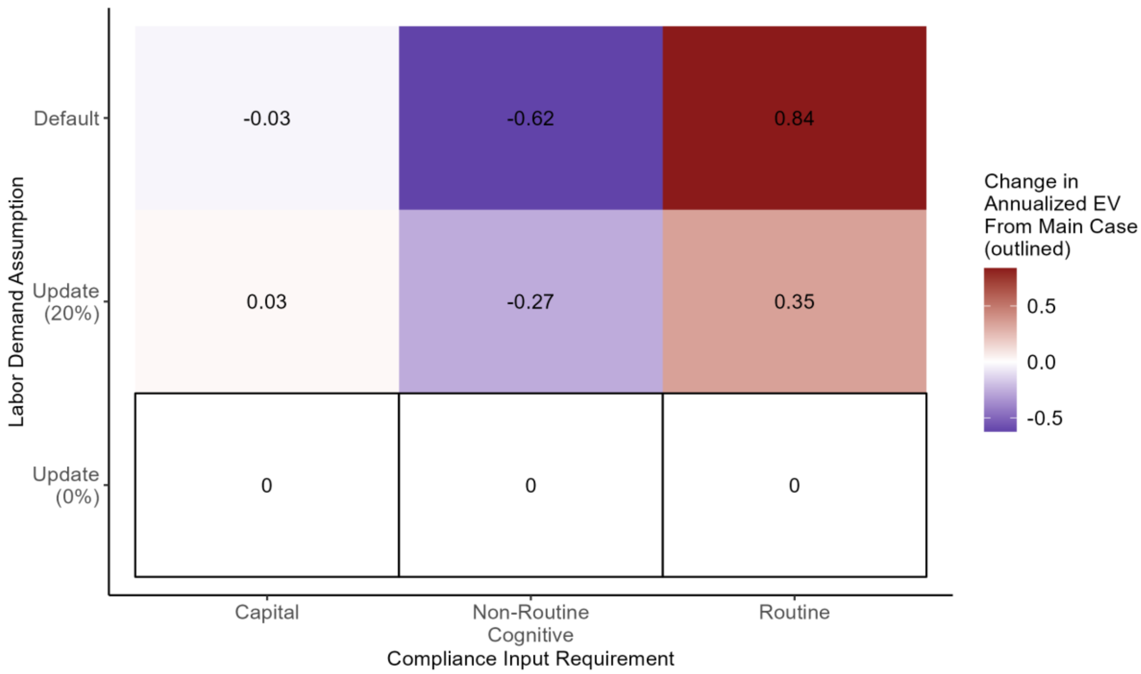

Figure 17: Change in Annualized EV From Main Simulation by Alternative Labor Demand Assumptions [Billion 2016$]

Figure 17 reports the difference in total annualized social costs between the main simulation, identified by bolded borders in the figure and an alternative specification of labor demand. As before, the figure is organized from top to bottom as most flexible to least flexible representations of labor demand. Deviations in aggregate social costs from our main simulations range from -3% to 4%. In all cases, adding flexibility to the demand for labor yields additional compliance pathways for regulated sectors relative to the “Update (0%)” case. When compliance input requirements are capital intensive, social costs are insensitive to the model’s labor demand structure. In these scenarios, alternative labor demand structural assumptions yield minor increases in aggregate social costs due to the relatively small difference in the amount of induced substitution between them.[38] When compliance is labor intensive, the change in social costs is dependent on occupational requirements. In the non-routine cognitive case, additional flexibility in the demand for labor reduces wage impacts for non-routine cognitive labor limiting labor supply decisions, which causes social costs to fall. In the routine case, the added flexibility provides an additional compliance pathway other than capital substitution. Social costs are greater given the net effect of a relatively smaller tax interaction effect complemented by a reduction in near term investment and long run consumption.

Underlying differences in aggregate social costs are changes in distributional impacts. Labor supply and/or demand flexibility will create differences in equilibrium wage rates, inducing changes to factor income, interactions with pre-existing distortions, and expenditures. Figure 18 reports the distributional impacts across labor demand and supply sensitivities. The sensitivities produce little differences in distributional impacts for the capital intensive shock. When compliance is routine-labor-intensive, more flexible labor demand shifts the burden of the regulation more towards lower income households as welfare gains from higher routine labor wages are mitigated through alternative factor substitution. Labor supply sensitivities produce few distributional differences in this case. Alternatively, when regulatory compliance is non-routine cognitive-intensive, labor demand and supply sensitivities can either exacerbate or change the sign of the welfare impact by household type. When labor demand and supply are more flexible, the gains from a relatively inelastic supply of non-routine cognitive labor is redistributed through substitution effects. Conversely, in the fixed supply case, the burden of the regulation shifts more toward lower income households.

[38] This effect could increase as the shock size increases. However, because most environmental regulations are smaller in magnitude than the modeled shock in this paper, we refrain from any explicit modeling of this assertion.

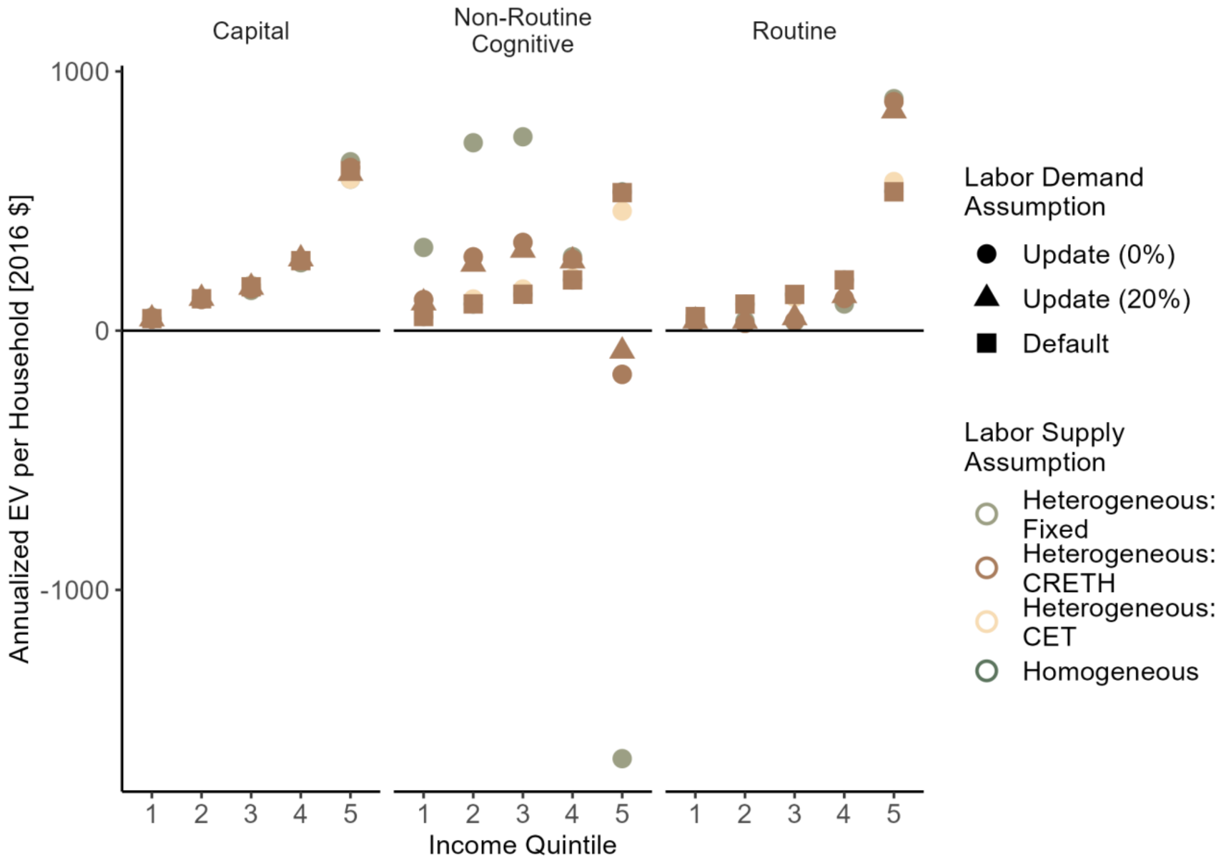

Figure 18: Annualized EV by Household and Labor Supply/Demand Assumption [2016$]

4.2 Sensitivity to Labor Mobility Assumption

The default assumption in the SAGE model is that labor is immobile across Census divisions. This assumption approximates the regional transitions reported by the Origin-Destination Job-to-Job Flows data by the Census Bureau (see Appendix A) and comports with recent evidence that shows a marked decline in interstate migration in the United States since the 1980s. Molloy, et al. (2014) noted that these observed declines in geographic mobility are highly correlated with decreases in labor market transitions (across both sectors and occupations) and pointed to evidence that declines in labor market transitions are related to higher costs (or lower benefits) for workers from changing employers. Kaplan and Schulhofer-Wohl (2017) pointed to improvements in workers' ability to learn about other locations before moving. As information has improved, the returns to specific skills have also grown more similar across labor markets. This has reduced the need for workers to move to maximize returns on their individual abilities.[39]

Despite these recent trends, it is still important to understand the sensitivity of our results to labor mobility assumptions. It is beyond the scope of this paper to attempt to model migration in SAGE. Doing so would require significant structural changes to accommodate household decisions on where to work and live (e.g., see Fan et al., (2018) for an approach for linking a CGE model with a sorting model) and assumptions about how preferences may or may not change after migrating. Rather, we construct a version of the heterogeneous occupations SAGE framework where the labor market clears at the national level rather than at the Census division level. This allows us to model labor market changes where households can choose to work in a model region that differs from where they live (e.g., full time remote work). This comparative framework provides bounds on the sensitivity of our results to labor market mobility assumptions since real-world mobility likely lies somewhere in between, though most likely closer to the default specification.

Reducing the rigidities in the labor market allows the model to find new opportunities to reduce the costs of the regulation. In comparing aggregate annualized socials costs between the labor mobility specifications, Table 9 shows that the national labor market closure reduces social costs across all compliance scenarios in the heterogeneous occupational framework. Furthermore, the wedge in social costs from between the two labor-intensive compliance scenarios diminishes.

Table 9: Sensitivity of Annualized Equivalent Variation to Labor Mobility [Billion 2016$]

	Labor Market Representation	
Compliance Input Requirement	Regional Labor Markets (default)	National Labor Market
Capital	27.7	26.4
Non-Routine Cognitive Labor	23.5	21.5
Routine Labor	22.0	21.5

[39] See also Davis and Haltiwanger (2014) and Molloy, et al. (2016) for further discussion of possible reasons for declines in labor market transitions and geographic mobility.

The national market closure provides regulated firms access to a pool of labor supply outside of their immediate region and therefore, the output effect is no longer constrained by the supply of labor in regional markets. Because the regulatory impact is not homogeneous across regions, regions with relatively less costly compliance requirements become more competitive and can increase output. Figure 19 shows the percent change in labor demands by regulated sectors in regions relatively less or more burdened by compliance costs and labor mobility assumptions. We define the former category as regions with less than 5% of overall compliance costs (East South Central, West North Central, Mountain, and New England) and the latter as all other model regions. Across all compliance scenarios, the national labor market assumption produces a redistribution of labor demand across the United States economy. Less regulated regions become more competitive in output markets and demand more labor. This contrasts with the default model labor market closure that restricts labor redistribution across regions.[40]

[40] This generalized summary may not be true for all unregulated sectors. Sectors not directly regulated but act as support sectors for those directly regulated are also relatively burdened by the regulation and can be associated with reductions in labor demand.

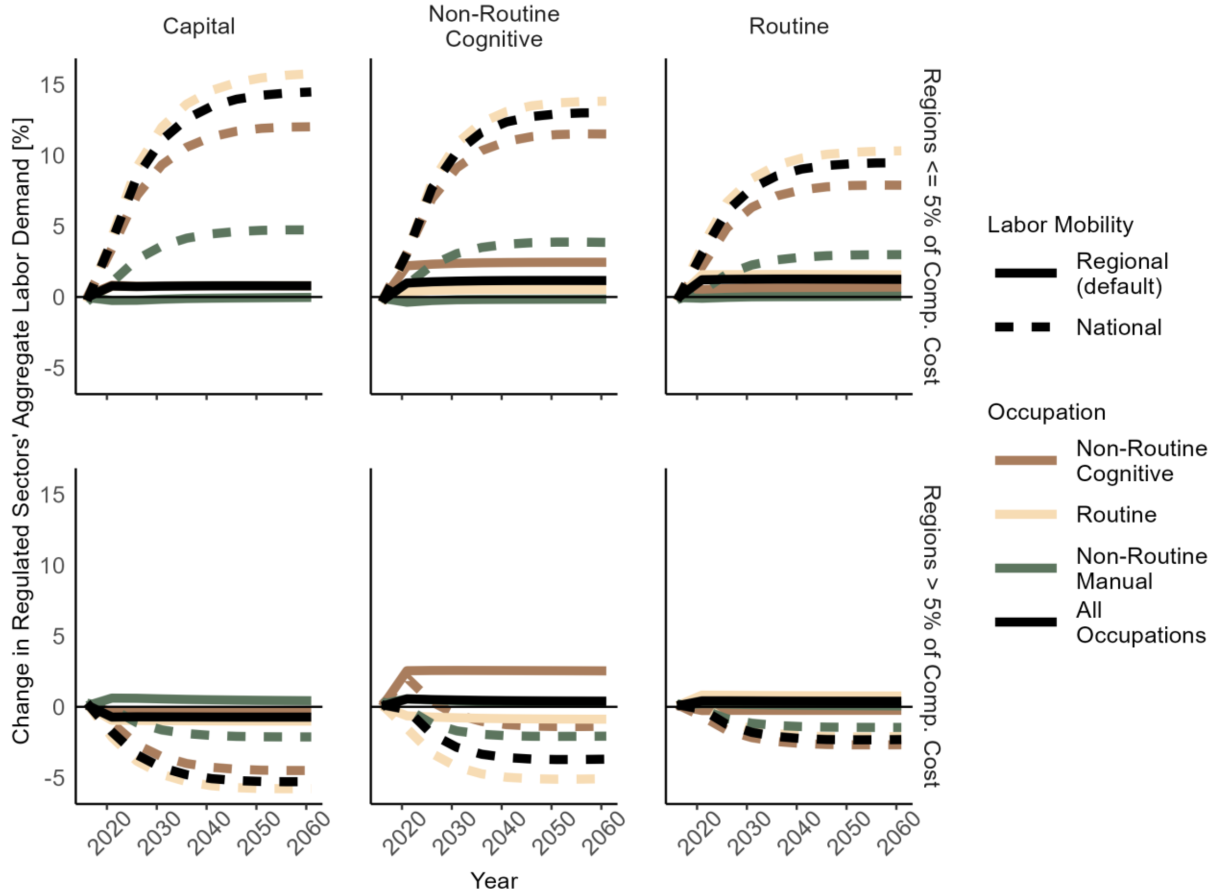

Figure 19: Change in Regulated Sector' Labor Demand by Labor Mobility

Figure 20 reports the change in the average national wage rates across labor mobility assumptions and compliance scenario. In the capital-intensive compliance scenario, greater access to additional labor allowing firms more opportunity to substitute away from capital toward routine labor to minimize costs more than when they were limited to the regional labor market. Aggregated to the national level, this causes a larger shift in wage rates by occupation. In the non-routine cognitive labor-intensive compliance scenario, the national level model produces relatively smaller changes in the returns to non-routine cognitive labor. The change in the return to cognitive labor is higher with a regional labor market closure because the supply of labor is relatively more inelastic since the costs of switching to a cognitive occupation are relatively higher than for other occupational categories. In the routine labor-intensive compliance scenario, the labor market closure differences are small because the supply of routine labor is relatively more elastic than the non-routine cognitive labor case allowing regional labor markets to better accommodate increases in labor demand for routine occupations.

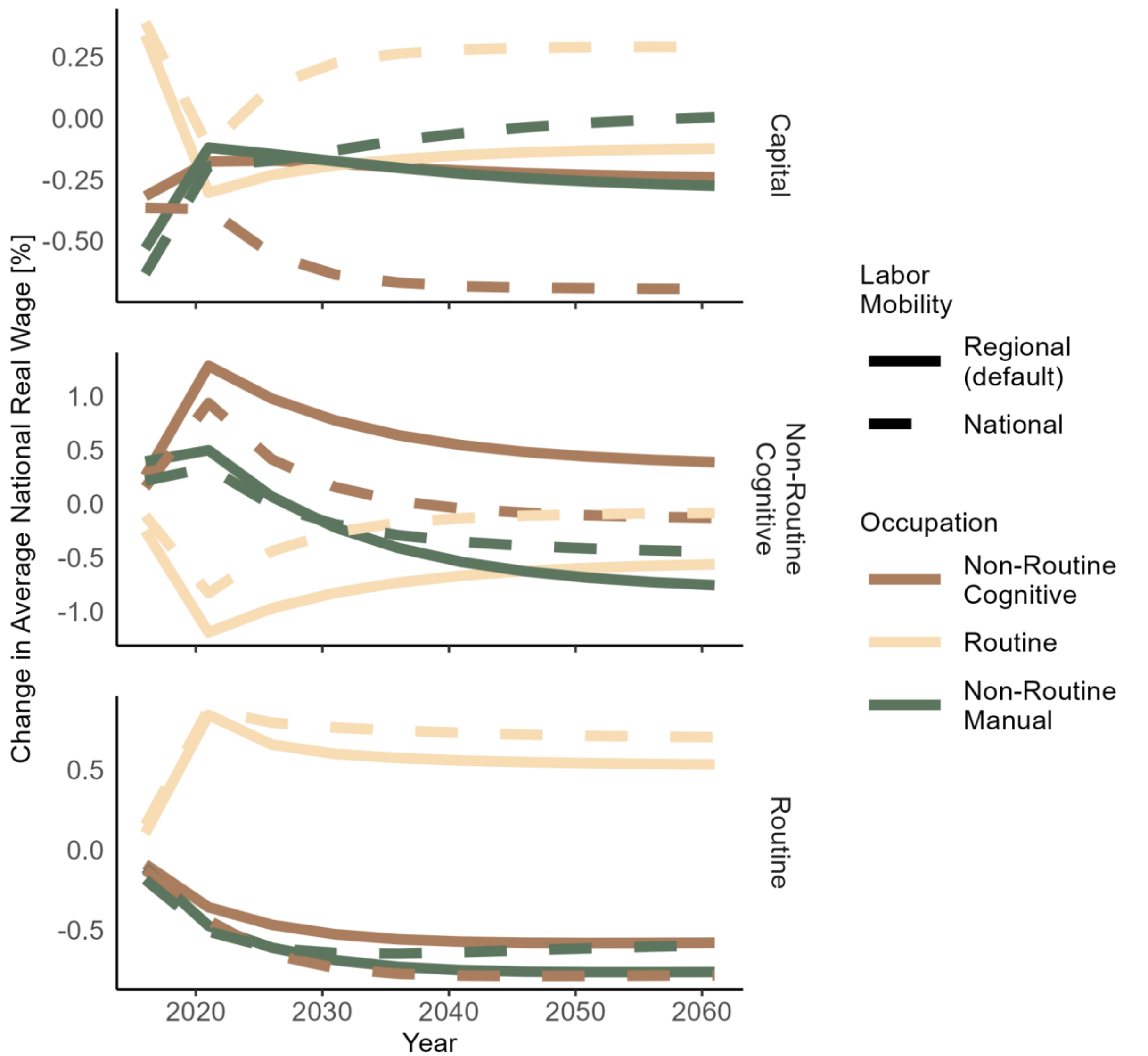

Figure 20: Sensitivity of National Wage Impacts Across Labor Mobility Assumptions

While a national labor market reduces aggregate social costs, it reallocates incidence across regions and households. The redistribution of social costs across regions is reported in Figure 21 as the change in household level equivalent variation relative to the regional labor market model (e.g., regions with EV to the right of the intercept have relatively higher costs in the national market model). Under both labor market representations, production shifts to regions with lower regulatory requirements. When labor is immobile across regions, wage rate increases in relatively unregulated regions are higher relative to when the labor market is closed nationally. Under a national labor market, wage increases in relatively unregulated regions are bid down from out of region workers. Furthermore, the national market closure effectively shifts production across regions but the returns to labor accrue to where people live (in potentially different regions). Therefore, prices increase in regions with increased output without commensurate changes in labor income from higher factor demands.

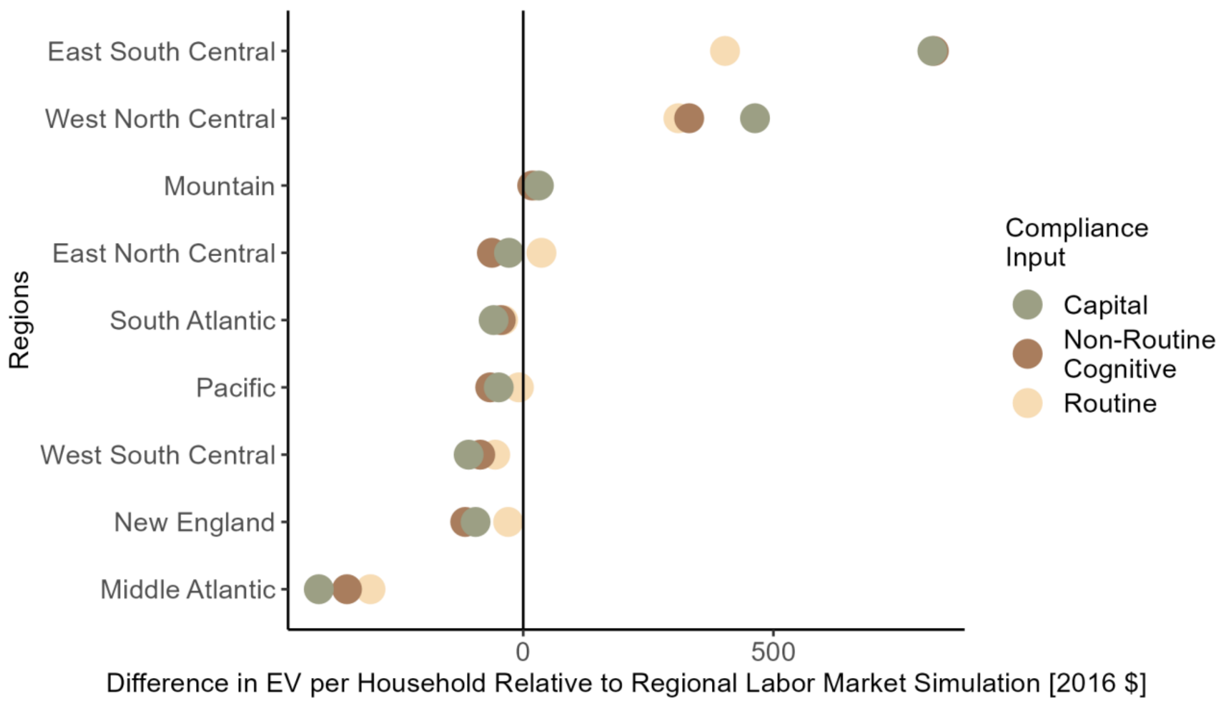

Figure 21: Redistribution of Equivalent Variation Across Regions and Scenarios by Labor Mobility

The differences observed in social costs across labor mobility assumptions largely are born by richer households as the primary owners of capital and main supplier of non-routine cognitive labor. Figure 22 reports the heterogeneous annualized equivalent variation impacts by region, income, input bias, and labor mobility assumption. Relative to the default regional labor market, the national market closure produces higher costs in regions with lower compliance costs and sometimes negative equivalent variation (welfare improvements) in regions with greater compliance costs, much of which is concentrated in households in the topmost income quintile.

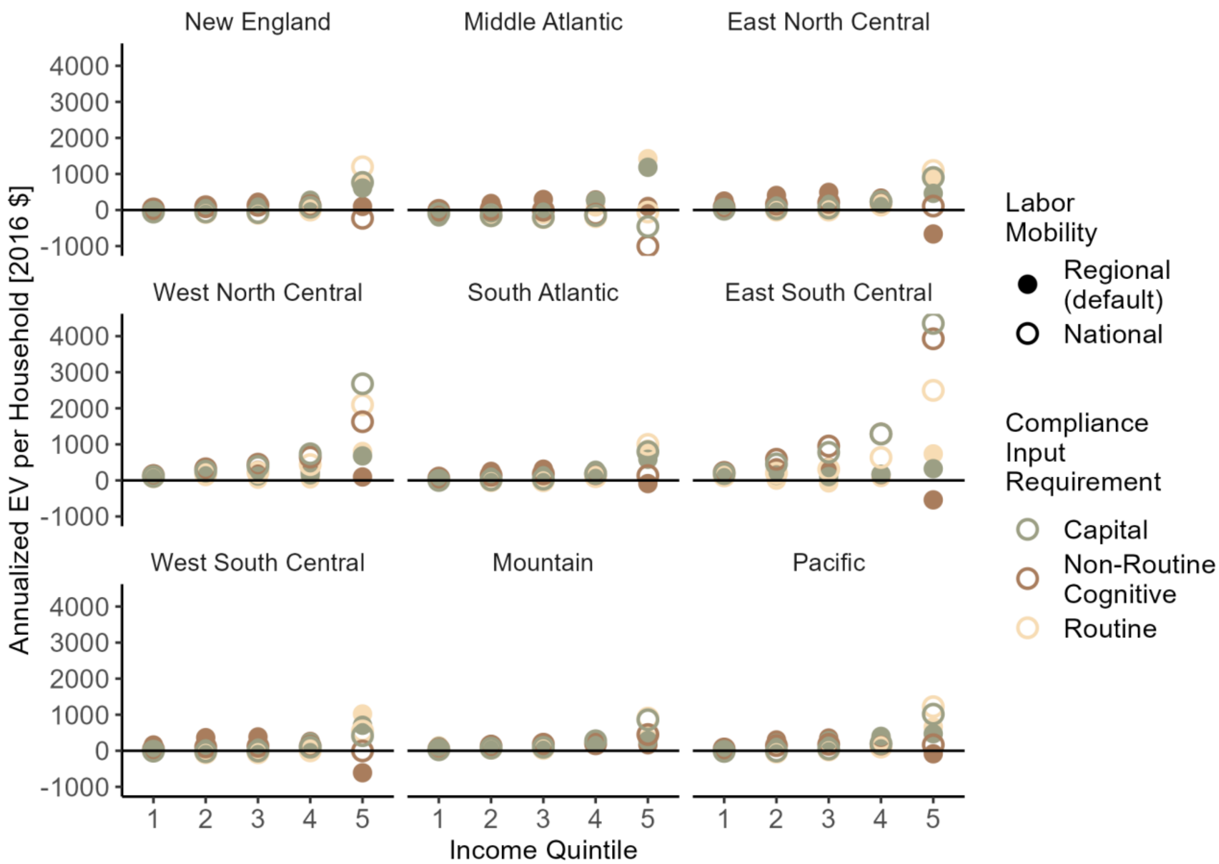

Figure 22: Annualized EV by Region, Income, Input Bias and, Labor Mobility

5 Concluding Discussion

In this paper, we augment the SAGE CGE model to consider the role of worker heterogeneity based on empirical estimates for labor supply and demand flexibility. In a case study of a large suite of environmental regulations promulgated under the Clean Air Act Amendments, we find that explicitly modeling occupational heterogeneity has a modest impact on aggregate social costs but a significant impact on how those costs are distributed across society. Our results suggest that if compliance activities require more non-routine cognitive occupations (e.g., engineers, managers, computer analysts, lawyers) the burden of the regulation can shift towards low to middle income households. Conversely, the burden shifts toward high income households if compliance requires additional capital investment or hiring workers in routine occupations (e.g., administrative staff, construction workers, trade technicians, transportation workers). In reality, every regulation will be unique in both the magnitude of compliance activities and the types of labor it may require. However, our results underscore the potential importance of seeking out additional information on labor requirements when evaluating the incidence of regulatory costs if compliance activity is expected to be labor intensive.

These findings are tested across a range of sensitivity simulations to tease out the importance of the labor supply and demand representation and parameterization, geographic labor mobility, and implementation of the economic shock. The sensitivities illustrate the importance of tying modeling assumptions to empirical evidence. First, simply incorporating additional occupational detail in a CGE model is insufficient for adequately capturing incidence of policy. We find that simple approximations of labor supply and demand decisions even with occupational detail in the model (e.g., perfect complements vs. perfect substitutes) can significantly under- or overestimate incidence on different household types relative to parameterizations calibrated to estimates from the literature. Second, the geographic labor market closure can significantly influence the regional incidence of a policy. Regions associated with higher compliance costs can shift the burden to regions with lower compliance costs if the labor market allows for "remote" work. Finally, we find relatively minor differences in results due to the regulatory representation in the model.

The methods developed in this paper are subject to several caveats. First, CGE models are most appropriate for characterizing the medium to long-run impacts of a policy. We extrapolate away from the possibility of transition costs in labor markets, for which there is a separate literature examining their importance (e.g., see Hafstead and Williams (2018)). Second, we assume that the elasticities governing labor supply and labor demand decisions are constant across time. In other words, the ease in which a household can switch from one occupation to another is the same today as it will be in the future. Similarly, the ability for firms to substitute between certain types of labor with capital is also time invariant. These relationships may change over time as advances in technologies can lead to additional substitution possibilities with all labor occupations (e.g., artificial intelligence being able to prepare legal documents, online education, etc.). Our results would likely be robust to this change if it were a long-run phenomenon taking several decades but may be sensitive if the transition happens faster. Third, an additional caveat is the treatment of capital in our simulations. SAGE has two types of capital (extant and new) that are both based on the same investment bundle from the underlying input output data structure which is a combination of different types of capital in the economy (buildings, computers, etc.). Simulations that assume capital-intensive compliance behavior implicitly assume that the capital requirements follow this investment bundle which may or may not appropriately characterize the input implications of regulatory requirements. For instance, if we assume a capital-intensive compliance approximates the installation of additional pollution control technologies, it may be the case that this would underapproximate the demand for engineers and overapproximate the demand for construction workers. Our incidence results for the capital-intensive compliance scenarios may shift if we are better able to characterize compliance equipment input requirements. We save these extensions for future research.

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Appendix A: Regional and Sectoral Transition Matrices

Table 10: Regional Transition Matrix (Census Divisions, 2010-2015)

		Destination								
		New England	Middle Atlantic	East North Central	West North Central	South Atlantic	East South Central	West South Central	Mountain	Pacific
		Nen	mat	enc	wnc	sat	esc	wsc	mnt	pac
Origin	nen	0.89	0.04	0.01	0.00	0.03	0.00	0.01	0.01	0.01
	mat	0.01	0.90	0.01	0.00	0.05	0.00	0.01	0.01	0.01
	enc	0.00	0.01	0.91	0.02	0.02	0.01	0.01	0.01	0.01
	wnc	0.00	0.00	0.03	0.89	0.01	0.01	0.02	0.02	0.01
	sat	0.01	0.02	0.01	0.00	0.91	0.01	0.01	0.01	0.01
	esc	0.00	0.00	0.03	0.01	0.05	0.87	0.03	0.01	0.01
	wsc	0.00	0.00	0.01	0.01	0.02	0.01	0.92	0.01	0.01
	mnt	0.00	0.01	0.01	0.02	0.01	0.00	0.02	0.88	0.05
	pac	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.03	0.92

Table 11: Sectoral Transition Matrix (2010-2015)

		Destination												
		Agriculture & Forestry	Mining	Construction	Manufacturing	Wholesale & Retail	Transport & Utilities	Information	Financial Activities	Professional & Business Services	Educational & Health Services	Leisure & Hospitality Services	Other Services	Public Admin.
		1	2	3	4	5	6	7	8	9	10	11	12	13
Origin	1	0.51	0.01	0.09	0.08	0.08	0.04	0.01	0.01	0.04	0.05	0.03	0.02	0.02
	2	0.02	0.37	0.14	0.11	0.06	0.08	0.01	0.02	0.07	0.04	0.03	0.03	0.02
	3	0.02	0.02	0.59	0.07	0.06	0.04	0.01	0.02	0.06	0.03	0.03	0.02	0.02
	4	0.01	0.01	0.06	0.38	0.12	0.06	0.02	0.04	0.11	0.07	0.04	0.04	0.03
	5	0.01	0	0.03	0.08	0.42	0.05	0.02	0.07	0.08	0.1	0.09	0.04	0.02
	6	0.01	0.01	0.06	0.11	0.13	0.36	0.02	0.04	0.09	0.06	0.04	0.03	0.03
	7	0	0.01	0.03	0.07	0.1	0.03	0.33	0.06	0.14	0.09	0.06	0.03	0.03
	8	0	0	0.03	0.06	0.12	0.03	0.02	0.37	0.14	0.11	0.05	0.03	0.04
	9	0.01	0.01	0.04	0.08	0.08	0.03	0.03	0.07	0.42	0.11	0.06	0.03	0.04
	10	0	0	0.01	0.03	0.05	0.02	0.01	0.04	0.07	0.62	0.06	0.04	0.04
	11	0	0	0.02	0.04	0.13	0.02	0.01	0.03	0.07	0.12	0.49	0.04	0.01
	12	0.01	0	0.03	0.06	0.09	0.03	0.01	0.03	0.08	0.16	0.08	0.37	0.03
	13	0.01	0	0.03	0.06	0.05	0.03	0.01	0.05	0.12	0.16	0.03	0.03	0.41

Appendix B: Model Calibration

The social accounting matrix is built from the 2016 state level accounts in the IMPLAN dataset.[41] The IMPLAN dataset is extended in three ways. First, ad valorem taxes for labor and capital income are added to the dataset (see Marten (2019) Appendix B for additional details). Second, oil and gas extraction is disaggregated into separate sectors for crude oil extraction and natural gas extraction using state level data on production and consumption by sector from the U.S. Energy Information Administration and trade data from the U.S. Census Bureau. Third, we use population estimates for each representative household by region from the U.S. Census Bureau's Current Population Survey.

The substitution elasticities for the production functions and Armington trade specification are adopted from recent empirical studies. The three KLEM substitution elasticities (*se_klem*, *se_kle*, and *se_kl*) are adopted from Koesler and Schymura (2015), while the substitution elasticities for the energy bundle (*se_ene* and *se_en*) are adopted from Serletis, et al. (2010). The Armington elasticities between the local-intra-national composite and intra-national imports (*se_nf*) are adopted from Hertel et al. (2008). To calibrate the Armington elasticity between local and intra-national imports (*se_dn*) and the transformation elasticity between output destinations (*te_dx*) we follow Caron and Rausch (2013). The price elasticities of supply used to calibrate the substitution between the KLEM composite and fixed factors in resource extraction and agriculture sectors (*se_rklem*) are adopted from additional sources. For natural gas extraction, crude oil extraction, and coal mining we follow Arora (2014), Beckman et al. (2011) and Balistreri and Rutherford (2001), respectively. For agriculture and forestry, we follow the Hertel et al. (2002). In the intra-temporal utility function the substitution elasticity between consumption and leisure (*se_cl*), along with the benchmark time endowment, are calibrated to match the midpoint of the ranges for the compensated and uncompensated labor supply elasticities in the review of McClelland and Mok (2012).[42] We adopt the substitution elasticities in the intra-temporal utility function's energy bundle (*se_cene*, *se_cen*) from Serletis et al. (2010). The remaining substitution elasticities in the intra-temporal utility function (*se_c*, *se_cm*, and *se_cem*) are adopted from Caron and Rausch (2013), who use the same nested CES specification. The inter-temporal substitution elasticity of full consumption is adopted from Goulder and Hafstead (2018). Additional details and specific parameter values are presented in Marten and Garbaccio (2018).

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[41] IMPLAN Group, LLC, 16740 Birkdale Commons Parkway, Suite 206, Huntersville, NC 28078; www.IMPLAN.com .

[42] The calibrated compensated labor supply elasticity is 0.2 and the calibrated uncompensated labor supply elasticity is 0.5 based on the midpoints in McClelland and Mok (2012).

The exogenous parameters defining expectations about the growth and structure of the economy in the baseline are derived from U.S. Energy Information Administration's 2018 Annual Energy Outlook (AEO). Economic growth is driven primarily by population growth and Harrod neutral (i.e., labor embodied) productivity growth. Both of these parameters are set to the average growth rates over the time horizon of the most recent AEO. Energy intensity improvements are assumed to be capital embodied and calibrated by shifting the future cost shares in the nested CES production functions to match the sector specific average growth rates of energy intensity of production reported in the most recent AEO. Consumption shares in the intra-temporal utility function are similarly shifted away from energy goods to approximate the average reduction in the share of real consumption expenditures on specific energy types as reported in AEO. Finally, the share of coal in electricity production is shifted towards capital and labor, to match the shift from coal fired generation to renewables in AEO (noting that the share of electricity generation from natural gas is expected to remain relatively constant in AEO thereby not requiring additional calibration).

Appendix C: Sensitivity to Regulatory Representation

Table 12 shows that the welfare costs are not particularly sensitive to the way in which compliance is characterized in the model. Introducing compliance as a collection of productivity shocks induces slightly smaller price impacts due to additional substitution possibilities allowed in the production framework. When the compliance requirement is capital-intensive, the productivity shock produces a slightly larger welfare cost. The productivity shock allows for a more flexible compliance mechanism, allowing firms to substitute capital for routine labor more than when regulation is represented as an explicit compliance requirement.

Figure 23 reports the distributional consequences of the productivity shocks across household types and policy representation. Added substitutability in the capital-intensive shock leads to a relatively larger reduction in household income for richer households who derive a larger fraction of their disposable income from the returns to capital.

Table 11: Sensitivity of Annualized Equivalent Variation to Policy Representation [Billion 2016$]

	Policy Representation	
Compliance Input Requirement	Compliance Requirement	Productivity Shock
Capital	27.7	28.6
Non-Routine Cognitive Labor	23.5	23.2
Routine Labor	22.0	21.6

When the compliance requirement is labor-intensive, the opposite happens. The productivity shocks produce relatively smaller social costs. In the routine labor-intensive compliance scenario, regulated sectors are afforded the possibility of substituting routine labor for capital relatively more with the productivity shocks leading to relatively smaller costs for upper income groups. The impact of policy representation on aggregate and distributional social costs are relatively smaller for the non-routine cognitive biased compliance scenario due to relatively limited substitution possibilities in the production functions.

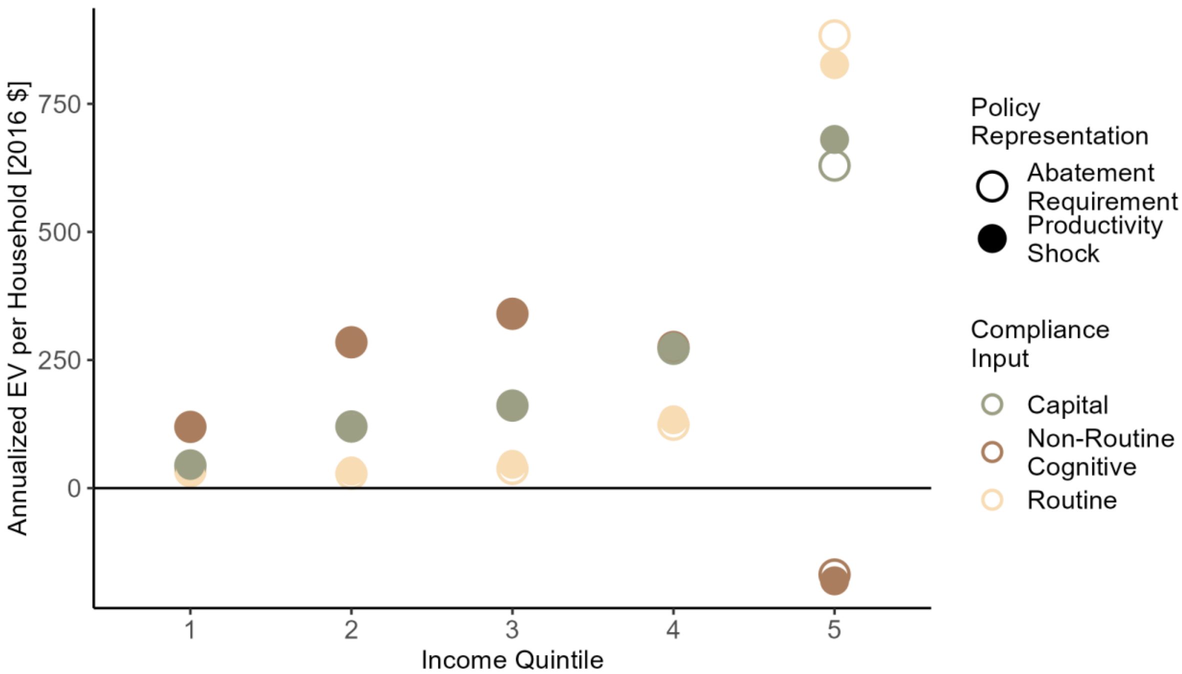

Figure 23: Sensitivity of Cost Incidence to Policy Representation