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Valuing Air Pollution's Impact on Labor Productivity in General Equilibrium*

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Abstract

This paper assesses the welfare implications of air pollution induced labor productivity improvements in a computable general equilibrium framework. We document that labor market productivity changes associated with a one $\mu g/m^3$ reduction in $PM_{2.5}$ can have a large welfare impact. Variation in the existing econometric evidence produces a range of possible welfare effects equal to approximately $950-3000 per household per year which is 50-160% of the estimated mortality impacts. Accounting for general equilibrium effects increases the welfare effect by roughly 45% relative to a back of the envelope estimate. Allowing for sector-specific shocks or impacts to leisure preferences have little effect on aggregate results. We also find that the aggregate welfare effect is approximately proportional to the shock size.

JEL Codes: C68, D58, Q51, J24

Keywords: CGE, health, air pollution, labor productivity

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1 Introduction

Air pollution causes millions of premature deaths worldwide every year (Burnett et al., 2018). In the United States, approximately 85 million people live with air above US EPA standards resulting in tens of thousands of premature deaths annually (EPA, 2023; Giannadaki et al., 2016). Air pollution has a wide array of other effects including heart attacks, strokes, asthma, reductions in cognitive performance, reductions in prosocial behavior, worsening mental health, and reductions in labor productivity (Lu, 2020; Aguilar-Gomez et al., 2022).

Prior studies on estimating the labor productivity effect of air pollution are based on econometric and other statistical approaches. The first vein of literature uses detailed data, typically comparing daily individual worker production measures to local measures of air quality, typically finding that a one $\mu g/m^3$ increase in $PM_{2.5}$ reduces labor productivity by about one percent. The second vein of literature uses aggregated data and generally finds that a one $\mu g/m^3$ increase in $PM_{2.5}$ reduces aggregate production by again approximately one percent. Estimates in each case range from tenths of a percent to almost two percent. The third vein of evidence is based in other fields including psychology and health sciences and provides mechanistic explanations for how air quality affects labor productivity.

In translating the estimated labor productivity effect into a welfare measure, existing literature has typically stopped short of deriving consistent welfare estimates inclusive of potentially important economy-wide effects. In this paper, we survey the existing literature to derive a plausible range of labor productivity effects from exposure to $PM_{2.5}$ in the United States. We use these estimates to parameterize labor productivity shocks to a large scale computable general equilibrium (CGE) model with detailed treatment of the United States economy to estimate the welfare implications of those changes in general equilibrium. We consider several modeling heterogeneities to assess the robustness of our results including sector differentiated shocks depending on levels of outdoor exposures, frictions in labor market constraining occupational mobility, and the importance of air pollution's effect on leisure demand. The approach allows for shocks to labor productivity in specific sectors, occupations, and regions.

CGE models provide a framework for translating estimated labor productivity effects into an aggregate welfare measure. Several attributes make them desirable for this exercise. First, the models are grounded in microeconomic theory. Welfare changes can be measured using metrics like equivalent variation as opposed to proxies like GDP. Equivalent variation avoids double counting and can be inclusive of both market and non-market based effects. Second, CGE models comprehensively account for all budgetary and resource constraints in the economy. This induces consistent treatment of consumption and savings decisions and associated effects on capital accumulation, interactions with pre-existing market distortions in the economy, fiscal impacts from changes in the tax base, and changes in trade balances (SAB, 2017). Finally, CGE models can characterize equilibrium effects across multiple sectors, households, regions, and time periods which can potentially be important if changes in air pollution exposure differentially affects segments of the economy or have effects which propagate across sectors and households.

Existing literature has illustrated the usefulness of CGE models for assessing the economy-wide costs of air pollution, showing that direct impacts to labor and leisure can lead to important long run equilibrium effects across the economy. For instance, several studies have attempted to estimate the economy-wide cost of air pollution by integrating specific health endpoint effects and expenditures into the model (Matus et al., 2008; Nam et al., 2010, 2019), or more collective measures of direct effects like impacts to available time, labor productivity, or agricultural productivity (Mayeres and Regemorter, 2008; OECD, 2016; Lanzi et al., 2018; Springmann et al., 2023), or seek to analyze specific policies inclusive of both policy expenditures and health improvements (Vrontisi et al., 2016).[1] Most of this existing work relies on global CGE models with relatively less detail for modeling the United States economy.

Our contribution to the literature isolates the importance of the labor productivity channel in the United States using a range of plausible effects based on recent econometrics estimates on the direct effect of air pollution on labor productivity. Existing CGE literature tends to focus on aggregate effects of air pollution that are inclusive of several underlying mechanisms (directly affected labor supply, productivity, expenditures). While there is limited information on the labor productivity channel specifically from these papers, benefit transfer is also particularly challenging when using CGE models

[1] A related literature in climate economics assesses the labor productivity effects of changes in temperature (e.g., Roson and Van der Mensbrugghe (2012); Hsiang et al. (2017)). There is also a large body of literature looking at labor productivity effects stemming from the costs of complying with environmental regulation (e.g., Gray et al. (2023)).

because model results are sensitive to several interacting aspects of the economy like tax structures, income levels, baseline productivity, etc. We note that Springmann et al. (2023) is most similar to this work which uses a CGE model to study the air quality impacts of dietary change globally finding significant GDP impacts. They use a multi-model approach that relates changes in diet to air quality impacts that are then fed into the CGE model through linear exposure-response functions based on a review of the econometrics literature on labor productivity. With exception of that paper, to our knowledge, existing studies are not representative of the latest econometric estimates.

This paper has three key findings. First, for plausible parameterizations, the impact of a one $\mu g/cm^3$ reduction in $PM_{2.5}$ on labor productivity has large welfare impacts ranging from \$950-3000 per household per year which is equivalent to 0.6-1.9% of full consumption. This is a large but not unreasonable change in $PM_{2.5}$. For comparison, the national average level of $PM_{2.5}$ declined by about five $\mu g/m^3$ from 2000-2020. Each additional unit reduction provides annual mortality risk reduction benefits of about \$1,900 per household. Second, we find that the general equilibrium estimates of welfare impacts are approximately 45% larger than a naive back of the envelope calculation that multiplies the labor productivity impact by a consistent projection of the value of baseline labor demand. Third, we find that the aggregate impacts are insensitive to heterogeneity in the way the labor productivity shocks are represented in the model.

In the remainder of the paper, Section 2 surveys the evidence on the effects of air pollution on labor productivity and discusses our parameterization. Section 3 describes the CGE model. Section 4 describes the scenario dimensions including model for modeling heterogeneous shocks across sectors and occupations. We discuss our results in Section 5 before concluding in Section 6.

2 Impacts of $PM_{2.5}$ Air Pollution

Air pollution, particularly fine particulate matter or $PM_{2.5}$, has massive effects on people's health and well-being worldwide (Cohen et al., 2017). It is a major cause of global premature mortality and causes asthma, heart attacks, strokes, and other illnesses (Cohen et al., 2017; U.S. EPA, 2022).

A large literature from the health sciences documents the effects of air pollutants on people's health (U.S. EPA, 2019, 2020, 2022; Aguilar-Gomez et al., 2022). The U.S. EPA's most recent systematic review of the effects of fine particulate matter found 'likely to be causal" or "causal" linkages between

$PM_{2.5}$ exposure and effects on the neurological, respiratory, and cardiovascular systems, as well as cancer and premature mortality. (U.S. EPA, 2019).

More recent evidence has also found that air pollution impacts people in ways that do not manifest as clinical health outcomes including worsened mood and mental health, reduced cognitive performance, reduced pro-sociality, and reduced subjective wellbeing (Lu, 2020; Aguilar-Gomez et al., 2022; Zundel et al., 2022). These sub-clinical effects result in social effects. Air pollution is associated with criminal activity (Bondy et al., 2020; Herrnstadt et al., 2021). Data from school testing provides evidence that air pollution is associated with worse performance on assessments (Heyes and Saberian, 2024). Data from non-physical competitions such as chess, e-sports, and "brain-training" games show worsened performance under higher levels of air pollution (Künn et al., 2023; Mo et al., 2023; La Nauze and Severnini, 2025). Air pollution has also been associated with worsened performance in marathons, soccer, and other sporting contexts (Lichter et al., 2017; Guo and Fu, 2019; Zacharko et al., 2021; Heintz et al., 2022).

Sub-clinical health effects can also reduce labor productivity. Micro-data economic studies provide detailed estimates of how air pollution affects workers' performance at specific work sites. These studies include indoor and outdoor workers, manual labor and desk jobs, and can measure productivity while working, number of hours worked, and mistakes made while working. There is evidence that air pollution negatively affects agricultural workers' productivity (Zivin and Neidell, 2012; Chang et al., 2016a). These effects are typically short term (daily or weekly), suggesting that this does not reflect long-term health problems. Air pollution is also found to reduce productivity, increase mistakes, and alter professional decisions in work settings that are not physically arduous (Archsmith et al., 2018; Huang et al., 2020; Kahn and Li, 2020).

Aggregate data studies typically attempt to estimate the relationship between economic production (GDP) and $PM_{2.5}$ concentrations. These studies typically use aggregated political (e.g. counties) or economic units (e.g. firms or factories) and annual average data.

There is also evidence that firms can and do mitigate the effects of air quality by altering their practices, for example by hiring more workers or reallocating tasks across workers (Adhvaryu et al., 2022). These changes can help maintain production levels, but only by increasing costs and thus still represent reduced productivity.

Table 1 lists a series of recent econometric estimates of the effect of $PM_{2.5}$ on labor productivity or production. Estimates from the U.S. reported here range from a change in productivity of -0.006 (or -0.6%) to -0.019 (or -1.9%) per $\mu g/m^3$ increase in $PM_{2.5}$.

Estimates based on aggregate production appear to be larger than measurements of worker-day production. These estimands differ in key respects. First, productivity estimates adjust for the extensive margin of hours worked. Other studies have found evidence of both a reduction in total hours worked and reallocation of work across time (Hanna and Oliva, 2015; Holub and Thies, 2023). Second, there is evidence that firms respond to changes in air pollution by reallocating tasks across workers (Adhvaryu et al., 2019). This suggests additional costs of adjustment not captured by productivity metrics. We leave modeling the extensive margin of labor supply and other adjustment mechanisms for subsequent work.

The estimates in Table 1 are from a variety of econometric papers. We have normalized them to describe the effect of a one $\mu g/m^3$ increase in $PM_{2.5}$. The outcome variable varies. Chang et al. (2016a) and He et al. (2019) measure individual production per unit time. Borgschulte et al. (2024) and Dechezleprêtre et al. (2019) describe aggregate production. Adhvaryu et al. (2019) uses an industry-specific productivity measure. When used to shock the CGE model, we assume that the model input describes how much less labor is needed to produce a fixed amount of output.

To reflect variation in both the estimated values and the estimands, we will consider a range of labor productivity effect sizes. We will focus on the range of estimates from the U.S. and model a one $\mu g/m^3$ increase in $PM_{2.5}$ as reducing labor productivity by between 0.6% and 1.9%. In some visualizations, we will select an example effect estimate of 1.0% for visual clarity. This will primarily be to focus on decomposing effects, such as differentiating between returns to labor and capital or differentiating between effects on different sectors.

Table 1: Econometric Estimates of $PM_{2.5}$'s Impact on Labor

Paper	Point Estimate	Units	Notes
US Studies			
Borgschulte et al. (2024)	-0.019	$\frac{\Delta Earnings}{\mu g/m^3}$	Aggregate analysis in U.S.
Chang et al. (2016b)	-0.006	$\frac{\Delta Earnings}{\mu g/m^3}$	Indoor workers in California
Non-US Studies			
Dechezleprêtre et al. (2019)	-0.0080	$\frac{\Delta GDP}{\mu g/m^3}$	Aggregate analysis in EU
Fu et al. (2021)	-0.0082	$\frac{\Delta Earnings}{\mu g/m^3}$	Aggregate analysis in China
He et al. (2019)	-0.1	$\frac{\Delta output}{\mu g/m^3}$	Manufacturing in China
Adhvaryu et al. (2019)	-0.00079	$\frac{\Delta productivity}{\mu g/m^3}$	Manufacturing in India

Notes: the point estimate can be interpreted as the increase in productivity per decrease in air pollution. All point estimates represent a fractional change in the numerator per unit change in the denominator. A value of 0.01 would represent a one percent change per $\mu g/m^3$ of $PM_{2.5}$.

3 Modeling Labor Productivity Improvements in a CGE Framework

In this paper, we assume that labor productivity improvements from reductions in air pollution concentrations are modeled by reducing the amount of labor required to produce one unit of output. As an example, Equation (1) describes a simplified constant elasticity of substitution (σ) unit production function with labor (l) and capital (k) inputs (written in calibrated share form).[2] We denote ϕ as a labor productivity index that can be used to "shock" the CGE model.

$$f(l,k) = \left(\theta^l \left(\frac{l}{\phi \bar{l}} \right)^{\frac{\sigma-1}{\sigma}} + (1-\theta^l) \left(\frac{k}{\bar{k}} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

Per Marten et al. (2024a), reducing ϕ by β and holding other inputs fixed would require a β x 100% reduction in labor to continue producing the same amount of output. We assign levels of β to be reflective of the empirical literature.

3.1 Model Description

We use the U.S. EPA's CGE model, SAGE (v2.1.1), which is an intertemporal dynamic model of the U.S. economy. This section provides a brief description of the modeling approach. The model is

[2] For more on calibrated equations in CGE models, see Rutherford (2002). We denote reference levels of each input quantity with an overline character.

fully documented in Marten et al. (2024a).[3] Table 2 summarizes model dimensions. The economy is modeled in 5-year time steps from 2016-2081 with twenty-three sectors that encompass the entirety of the U.S. economy with resolution particularly focused on the energy and manufacturing sectors. The model also captures heterogeneous households denominated by income and sub-national resolution in the form of four Census Regions where each region has region-specific production functions and household preferences for the five household income types.

Table 2: SAGE Dimensions

Time Periods	**Sectors (abbreviations)**	**Census Regions**	**Households (income 2016$)**	**Capital Vintage**
2016-2081	Agriculture, forestry, fishing and hunting (`agf`)	Northeast	<30k	Extant
(5-year	Crude oil (`cru`)	South	30-50k	New
time steps)	Coal mining (`col`)	Midwest	50-70k	
	Metal ore and nonmetalic mineral mining (`min`)	West	70-150k	
	Electric power (`ele`)		>150k	
	Natural gas (`gas`)			
	Water, sewage, and other utilities (`wsu`)			
	Construction (`con`)			
	Food and beverage manufacturing (`fbm`)			
	Wood product manufacturing (`wpm`)			
	Petroleum refineries (`ref`)			
	Chemical manufacturing (`chm`)			
	Plastics and rubber products manufacturing (`prm`)			
	Cement manufacturing (`cem`)			
	Primary metal manufacturing (`pmm`)			
	Fabricated metal product manufacturing (`fmm`)			
	Electronics and technology manufacturing (`cpu`)			
	Transportation equipment manufacturing (`tem`)			
	Other manufacturing (`bom`)			
	Non-Truck Transportation (`trn`)			
	Truck transportation (`ttn`)			
	Services (`srv`)			
	Healthcare services (`hlt`)			

SAGE models sectoral production assuming perfectly competitive representative firms maximize profits subject to technology restrictions. The model distinguishes physical capital by its age to limit the transition of existing capital already present in the reference year (i.e., first time period of the model) between sectors and production processes. This approach, called partial putty clay, models existing (or extant) capital as relatively inflexible in its ability to accommodate changes in production processes and

[3] SAGE has been peer reviewed by the EPA's Science Advisory Board (SAB) to ensure that the model is consistent with economic theory and reflects the latest science (SAB, 2020). For the EPA's responses to SAB comments, see `https://www.epa.gov/node/266413`.

cross-sectoral uses relative to new capital, which can be shifted across sectors and substituted with other inputs. Production with extant capital is assumed to follow a Leontief structure where inputs are used in fixed proportions. Production with new capital is modeled as a nested constant elasticity of substitution (CES) functions that differentially characterizes substitution possibilities between classes of inputs. CES functions are used widely in general equilibrium modeling for their parsimony and global regularity properties (Brockway et al., 2017). For non-resource sectors, the top level nest combines non-energy intermediate inputs with a value added-energy composite. The model assumes a capital-labor-energy composite structure that is consistent with empirical data (Van der Werf, 2008). All substitution elasticities governing the substitution possibilities are either adapted from the best available estimates in the literature or estimated. For resource extraction (crude oil, natural gas, coal, and other mining) and agriculture sectors, the model assumes an additional factor input to represent finite natural resources that is calibrated to supply elasticities from the literature.

Households are assumed to maximize their intertemporal welfare subject to a budget constraint composed of factor incomes and transfers. Intertemporal welfare consists of a discounted stream of iso-elastic utility across modeled years. The model features a labor-leisure choice, meaning intratemporal utility is characterized over full consumption. Intratemporal utility is represented as a nested CES-LES (linear expenditure system) function calibrated to labor supply elasticities (McClelland and Mok, 2012) and estimated income elasticities using a methodology adapted from Aguiar and Bils (2015). A single government agent representing local, state and federal entities is assumed to levy taxes on labor and capital earnings and production in the form of indirect business taxes. Marginal and average tax rates on labor and capital earnings are estimated using TAXSIM.[4] The model assumes a balanced government budget, inclusive of an exogenous debt projection, such that any budget excess or shortfall in response to a policy shock is recycled as lump sum payments to or from households. Households are endowed with factors of production (e.g., time and capital) on which they earn incomes. Population, and in turn the time endowment, grows exogenously over time and households are assumed to supply labor within the region in which they reside. Household ownership of capital stock grows endogenously through savings, where household investment is mobile across regions. However, once installed, capital is assumed to be fixed to a model region (independent of its vintage). New capital stock is augmented

[4] http://users.nber.org/~taxsim/taxsim27/.

through investment in the previous period.

SAGE models the U.S. economy as a large open economy allowing for changes in the U.S. to impact world prices. The approach used in the model is calibrated to price elasticities consistent with an international economy modeling framework (Schreiber et al., 2024). The model characterizes import demand from and export supply to the international economy using the Armington assumption that defines preferences for regionally differentiated goods (Armington, 1969) with elasticity estimates from Aguiar et al. (2016). Trade within the U.S. is modeled as a pooled national market.

Growth in the economy is assumed to be driven by Harrod-neutral (e.g., labor augmenting) technological progress. Baseline aggregate economy-wide labor productivity growth is calibrated to the Congressional Budget Office's (CBO) Long-term Budget Projections. The model also assumes that future productivity growth is heterogeneous across the economy through sector differentiated labor productivity growth rates based on historical averages from Garner et al. (2021).

The SAGE model is based on several underlying datasets and projections. The core economic accounts are based on 2016 social accounting matrices from IMPLAN Group LLC. (2016) which are augmented to reflect economic estimates from the Energy Information Administration, Department of Interior, Department of Agriculture, Bureau of Economic Analysis, Census, Bureau of Labor Statistics, Congressional Budget Office, and the National Bureau of Economic Research. The model is solved as a mixed complementarity problem akin to Rutherford (1995).

3.2 Modeling Extension: Occupational Choice

The default SAGE model assumes a single type of labor that is substitutable with capital in the subnest of the production function with new capital. Because air pollution is likely to affect different types of workers heterogeneously depending on their level of exposure, how easily workers and firms can shift between more or less exposed occupations may be important determinants of equilibrium responses in labor and capital markets. Empirical evidence has suggested that limits to occupational mobility among relatively unskilled workers has played an important role in wage and job polarization in the United States in the past several decades (Acemoglu and Autor, 2011; Cortes, 2016).

We consider the labor market extensions to SAGE in Marten et al. (2024b) to study the importance of occupation mobility in the case of air pollution induced labor productivity effects relative to the default version of the model. Marten et al. (2024b) augments the SAGE model to explicitly account for occupational mobility restrictions in both the demand and supply for labor. The model extension captures occupational heterogeneity for three types of occupations: "routine" (r) or labor that performs tasks that are algorithmic and could be substitutable with capital, "non-routine cognitive" (c) or higher skilled labor, and "non-routine manual" (m) or labor with manual tasks that are difficult to routinize. Non-routine labor are treated as complements to routine labor and capital (Figure 1). We calibrate the substitution elasticities by setting $\sigma_{kl} = 0$ and adjusting σ_{klr} such that aggregate labor and capital substitutability mimics the default version of the model.

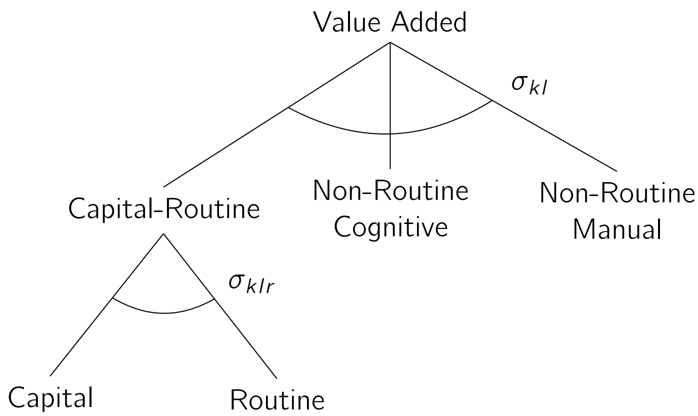


Figure 1: Disaggregated Labor Demand

The occupational extension captures labor supply transformations through a CRETH (Constant Ratio of Elasticity Transformation, Homothetic) function which allows for asymmetric switching costs between occupations (Figure 2). The function parameters are calibrated to approximate wage changes from Cortes (2016). We augment the default social accounting matrix in SAGE using data from the Current Population Survey's Annual Social and Economic Supplement from Census to disaggregate labor supply by household and occupation and using data from the Occupation Employment and Wages Survey (OEWS) from the Bureau of Labor Statistics (BLS) to disaggregate labor demand by sector and occupation. See Marten et al. (2024b) for more information on the disaggregation and parameterization of these functions.

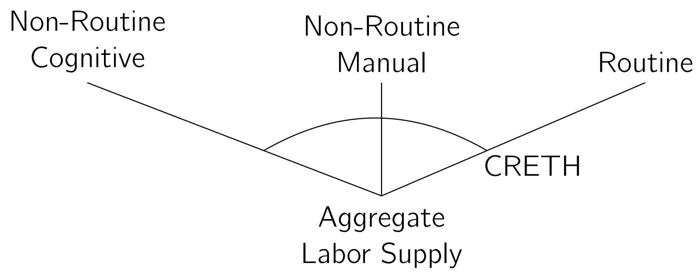


Figure 2: Household Labor Transformation

4 Scenarios

This section describes different shocks we provide to the base model of Section 3. In each shock, we model a one $\mu g/m^3$ uniform reduction in $PM_{2.5}$ across the United States that begins in 2026 and continues into perpetuity. We have three scenarios in how we model the labor market effects, listed in the top panel of Table 3.

In our first scenario, `Core`, we assume that the labor productivity shock applies uniformly across all sectors. In our `Sector Differentiated` experiment, the distribution of labor productivity shocks is based on outdoor exposures of the sector's workforce based on data from the Department of Labor (DOL). The `Occupational Frictions` scenario leverages the same input data as the sector differentiated shock but incorporates occupational mobility frictions in the model from Marten et al. (2024b).

We run our scenarios for a range of plausible changes to labor productivity (*LP Effect*) stemming from our review of the econometrics literature in Section 2. These reflect aggregate changes to labor productivity. In the `Sector Differentiated` and `Occupational Frictions`, the shock will vary as described in Section 4.1 with the average shock being varied over the range `0.1-2%`.

For our main scenarios, we assume that the labor productivity effect applies to the supply side of the model only (leaving the value of leisure unchanged). Section 4.2 discusses how we relax this assumption.

Table 3: List of Experiments

Scenario Dimension	Experiment	Description
Model Heterogeneity	`Core`	Uniform shock to economy-wide labor productivity.
	`Sector Differentiated`	Sectorally heterogeneous labor productivity shocks due to outdoor exposure.
	`Occupational Frictions`	Occupationally heterogeneous labor productivity shocks due to outdoor exposure with labor market frictions in occupational mobility from Marten et al. (2024b).
LP Effect	`0.6-1.9%`	Range of labor productivity improvements from a one $\mu g/m^3$ reduction in $PM_{2.5}$. See Section 2 for a review of the literature.
Labor/Leisure	`Leisure shocked?`	Explore the importance of make leisure more productive akin to the shock on the supply side of the model.

4.1 Sectoral and Occupational Shocks

We calculate sectorally and occupationally heterogeneous shocks based on information of outdoor air exposure. First, we calculate occupation-specific shocks in which occupations which are more exposed to outdoor work experience higher productivity shocks. The effects of air pollution on labor productivity may vary with occupation. While $PM_{2.5}$ generally penetrates building envelopes, outdoor workers may nonetheless be more exposed to air pollution. We construct occupation-specific measures of outdoor work intensity based on the U.S. DOL O*NET database.[5] We then assume that occupational exposures are proportionate to the outdoor work intensity index and calculate occupational productivity shocks that are proportional to the outdoor work intensity while maintaining the weighted average labor productivity effect (β).

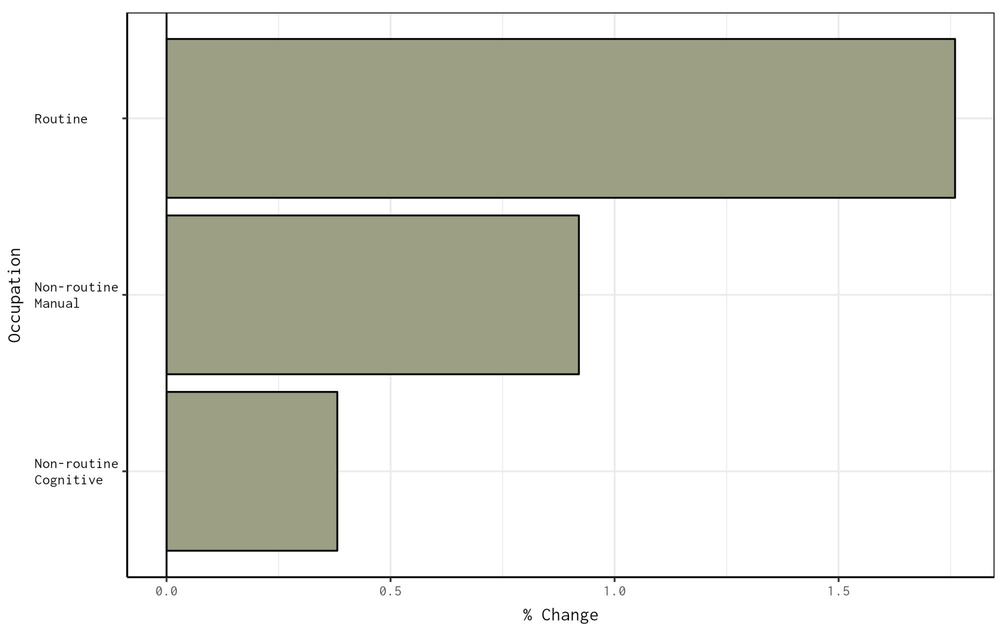
Occupations-specific outdoor work indices are generated for two-digit SOC code occupations based

[5] https://www.dol.gov/agencies/eta/onet

on detailed O*Net data. We start with O*Net's detailed six digit occupational data, which includes groups such as "Electricians", "Roustabouts, Oil and Gas", "Economists", "Sales Managers", and "Cashiers". The six digit occupations are aggregated to two digit categories such as "Management", "Protective Service", and "Production". For each six digit occupational group, we calculate the average fraction of days working outside.[6] We then average this frequency at the two digit SOC code, weighting by employment within the six digit code, and calculate the ratio of each frequency to the average.

We then scale each two digit SOC code's productivity shock by multiplying the average β by each group's outdoor work frequency relative to average. For example, workers in "Installation, Maintenance, and Repair" report working outside 2.15 times as frequently as average, so their β in the differentiated scenarios would be 2.15 the average shock. Figure 3 reports aggregated labor productivity estimates for the three occupational categories that are modeled in the occupational frictions scenario for the 1% shock scenario.

Figure 3: Occupational Frictions Productivity Shock (LP Effect=1%)



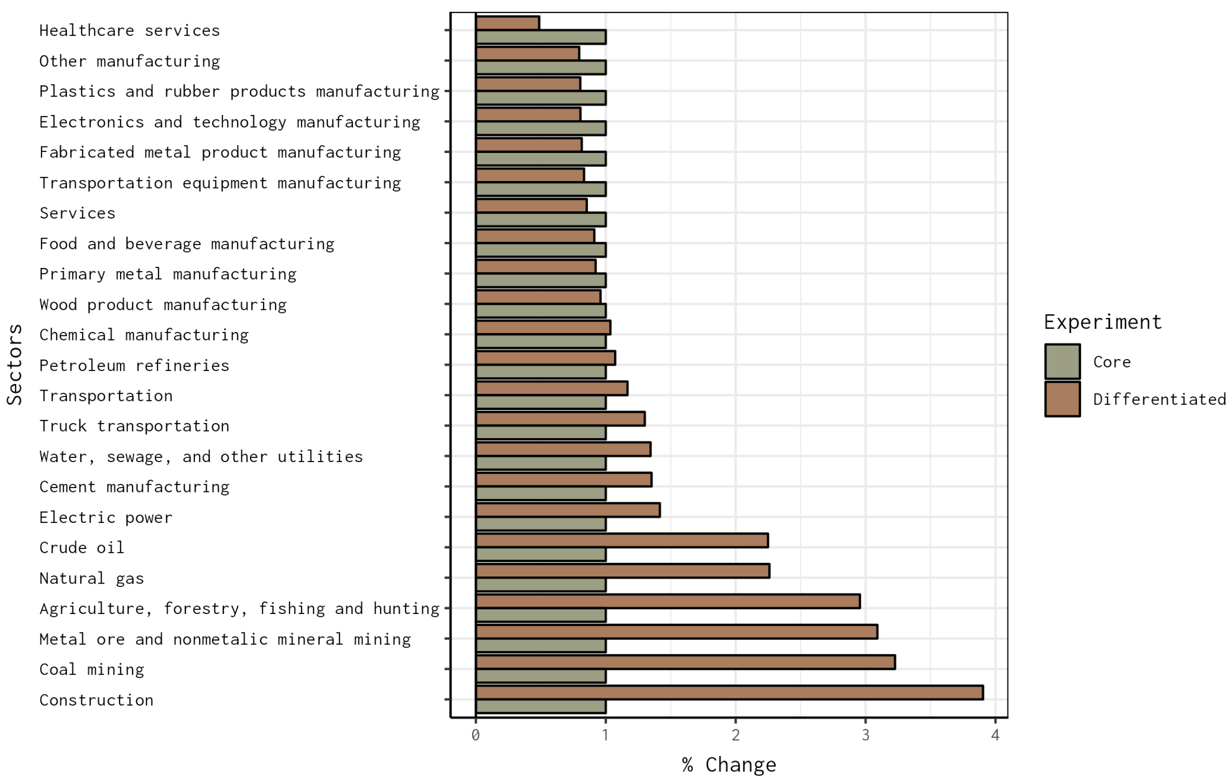
In the sector differentiated scenario, we allocate labor from occupations to sectors based on BLS OEWS data. This dataset provides an estimate of the fraction of each sector's labor demand which is from each occupational group. For each sector, we calculate the average shock based on its

[6] This analysis assumes that workers who report working outside at least weekly, monthly but not weekly, or annually but not weekly all actually work outside exactly once per week, month, or year respectively.

occupational mix. We calibrate both the sectorally differentiated shock and occupational friction shock such that the average impact is equivalent to the Core model scenario.

Figure 4 shows the sectorally varying shocks, along with the average 1% shock for the Core scenario. We see that healthcare, some specialty manufacturing, and services have below-average shocks, while outdoors-focused industries such as construction and extractive industries have the highest shocks. The average shock is equal to 1% in both scenarios

Figure 4: Sector Differentiated Productivity Shock (LP Effect=1%)



4.2 The Labor-Leisure Tradeoff

Air pollution may affect the value of leisure time. Econometric evidence suggests that people reduce outdoor activities when air pollution is high (Saberian et al., 2017; Chan and Wichman, 2020; Sun, 2023), and the socio-cognitive effects of air pollution may also affect the utility from indoor leisure activities. Omitting this effect may ignore an important response margin and lead to an inaccurate characterization of the labor-leisure tradeoff. However, it is unclear how to parameterize the effect of $PM_{2.5}$ on the return to leisure. We therefore conduct a sensitivity analysis in which we modify our

Core experiment by shocking the value of leisure time akin to the shock to labor productivity.

We do so by augmenting a preference index in each household's utility function over full consumption. Like Equation 1, and normalizing the benchmark utility index to unity as in Rutherford (2002), assume a unit utility function for consumption (c) and leisure (ls). We denote ϕ^{ls} as the preference index used to modify preferences for leisure.

$$u(c, ls) = \left(\theta^c \left(\frac{c}{\overline{c}}\right)^{\frac{\sigma^{cl}-1}{\sigma^{cl}}} + (1-\theta^c)\left(\frac{ls}{\phi^{ls}\overline{ls}}\right)^{\frac{\sigma^{cl}-1}{\sigma^{cl}}}\right)^{\frac{\sigma^{cl}}{\sigma^{cl}-1}} \tag{2}$$

Similar to the labor productivity shock, we reduce ϕ^{ls} by β, holding preferences for consumption fixed, which requires a $\beta x100\%$ reduction in the demand for leisure to achieve the same level of utility. Because utility is an ordinal measure, it is unclear how to calibrate the size of β. For this reason, we assume an identical shock size as the labor productivity shock.

5 Results

This section discusses our results. Section 5.1 describes results from our Core scenario. For ease of exposition and comparison, we will choose to focus on a single labor productivity shock in presenting some results. In these cases, we will use the example value of 1%. We find that the effects of shocks to labor productivity are large - labor productivity shocks of 0.6% and 1.9% have equivalent variation of \$946.9 and \$3028.7 per year, respectively. That is approximately 50% and 160% of the value of avoided mortality due to a one $\mu g/m^3$ reduction in $PM_{2.5}$.[7]

Sections 5.2 and 5.3 explore sensitivities to various extensions to the model. The aggregate welfare results are consistent across alternative specifications, although impacts vary across sectors and households. Unless otherwise specified, the results below assume that the assumed reduction in air pollution affects the productivity of labor but not leisure.[8]

[7] The value of avoided premature mortality is approximately \$1,900. However, the calculations use different analytic years and approaches to discounting, which limits the comparability of the values. Appendix A discusses the calculation of the valuation of avoided premature mortality.

[8] Appendix B presents additional results.

5.1 Core Scenario

This section presents results from our Core scenario. We find that the welfare effects of labor productivity shocks are substantial. These changes are regressive, with larger gains going to wealthier households. Gains from capital income exceed the gains from labor income in aggregate. Capital income primarily accrues to the wealthiest households.

Table 4: Welfare Impacts per Household

LP Effect (%)	*Annual Back of the Envelope ($)*	*Annual Equivalent Variation (EV, $)*	*EV % of Full Consumption*
0.6	652.3	946.9	0.6
1.0	1087.1	1583.0	1.0
1.9	2065.5	3028.7	1.9

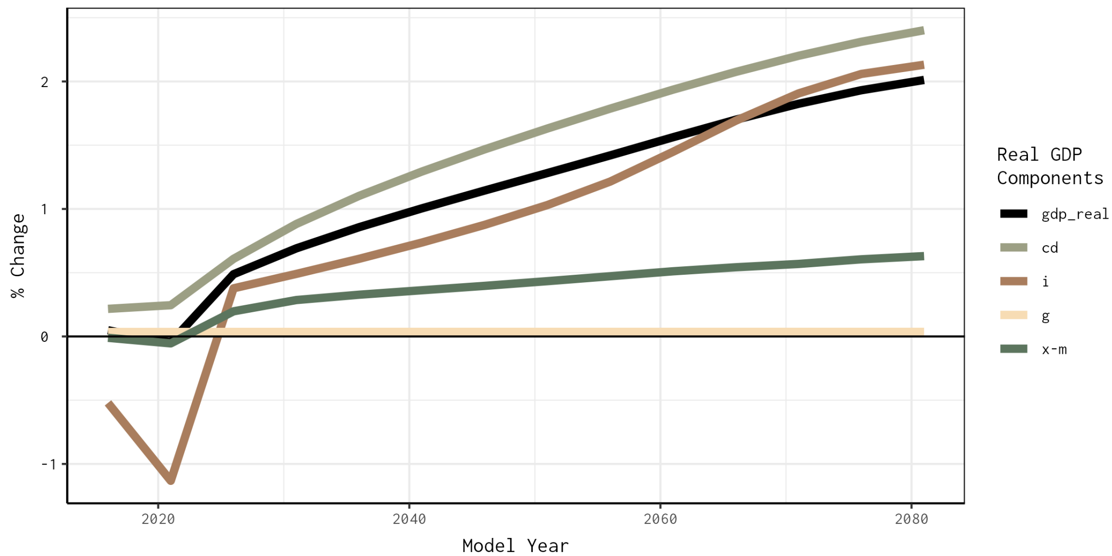
Notes: Annualized per household EV is calculated assuming an infinite time horizon and annualized based on a 4.5% discount rate which is approximately the internal discount rate used in the SAGE model. The back of the envelope calculation is similarly an annualized metric which multiplies the labor productivity effect by the labor share of production where we also assume an infinite time horizon and discount rate 4.5%. All values are in 2016 dollars and discounted back to 2016.

Table 4 shows households' annual average equivalent variation as calculated based on the uniform productivity shock and a naive partial equilibrium back of the envelope calculation in which the labor productivity shock is multiplied by the baseline labor share of production (discounted equivalently to EV). We see that the equivalent variation is large, proportional to the labor productivity shock, and approximately 45% larger than the naive calculation. The value of equivalent variation differs from the back of the envelope calculation due to equilibrium responses that affect reallocation across sectors, trade, aggregate investment, and economic growth. Furthermore, the CGE model captures tax interaction effects that can be important determinants of the overall welfare change (Williams III, 2002; Marten et al., 2019).[9] We find that a 1% labor productivity shock yields annual equivalent variation of $1,583 or 1% of full consumption. Larger and smaller shocks to labor productivity yield proportionately larger and smaller impacts.

Figure 5 reports the change in real GDP and its expenditure components. The shock is implemented as a fully anticipated change to labor productivity in 2026 into perpetuity by assuming less labor is

[9] Williams III (2002) finds that labor productivity improvements from reductions in pollution create a benefit-side tax interaction effect substantially increasing welfare effects.

Figure 5: Real GDP and Components (LP Effect=1%)



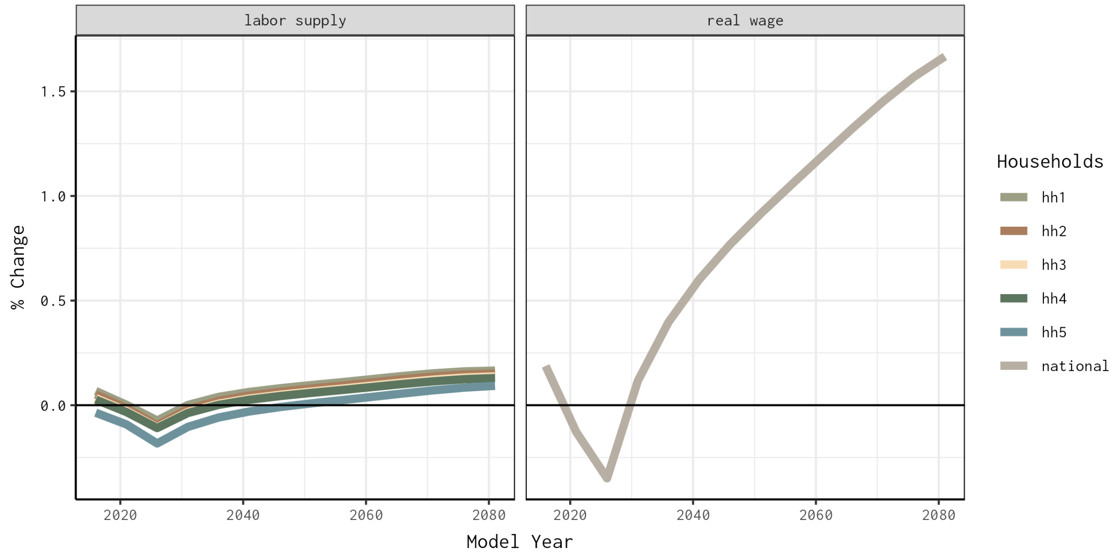
needed to produce a unit of output. The SAGE model is a perfect foresight model and therefore captures anticipatory behavior before the imposition of the shock. Generally, more productive labor expands the economy causing incomes to rise and prices to fall into the future relative to the baseline, including the cost of capital.[10] Increasing the productivity of labor induces additional demand for the value-added bundle in production increasing demand for both labor and capital. The percent change in real GDP is positive and increasing since the improvement in labor productivity spurs additional growth through increased investment and associated capital accumulation. Households reallocate their consumption (cd) and savings (i) initially in anticipation of those equilibrium effects. Falling output prices reduce the price of exports in the economy causing a slight rise in the value of real net exports (x-m).[11] The assumed closure rule in the model holds real government expenditures fixed (g).

Figure 6 shows the impact on labor supply and real wage rates over time. The shock initially reduces labor supply in 2026 which rebounds and increases relative to baseline levels over time. Frictions in the model like partial putty clay and fixed resource factors prevent the model from allowing instantaneous adjustments in the new equilibrium. As the model builds new, malleable capital over time, labor supply is relatively less constrained. Real wage rates, measured relative to the CPI, follows the general path of

[10] Figure 18 reports the change in the consumer price index (CPI) in Appendix B.

[11] We find that terms of trade falls in response to the labor productivity shock (Figure 17 in Appendix B). This causes a negative welfare effect since less of the imported variety can be purchased for each exported good (Schreiber et al., 2024). However, the terms of trade effect on welfare is relatively small. The large open economy specification of SAGE produces a positive welfare change approximately 3% smaller than a small open economy version of SAGE that assumes away terms of trade effects.

Figure 6: Labor Supply and Wage Relative to CPI (LP Effect=1%)



labor supply. However, because labor supply is relatively inelastic (subject to an exogenously growing time endowment split between labor and leisure), real wage increases are relatively larger, and more than the labor productivity shock size.

Figures 7 and 8 show variation in sectoral outcomes by output and real output price, respectively for model years 2026, 2036, and 2046. While the Core scenario imposes a uniform labor productivity shock across the economy, the model incorporates heterogeneous supply responses across sectors. For instance, the model constrains the production of sectors reliant on a natural resource (e.g., crude oil, natural gas, land). Therefore, constraints on output in these sectors leads to larger price effects to mitigate the demand response relative to sectors that are able to more readily expand (e.g., healthcare). Output and price effects increase over time.

Figure 9 shows equivalent variation by household for a range of labor productivity shocks. We see that equivalent variation increases with households' baseline income with a similar distribution across labor productivity shock sizes.[12] Estimated equivalent variation combines both income and expenditure effects in the model.[13] Households benefit from both reductions in goods prices as well as rising incomes from labor and resource endowments, capital investments, and transfer payments. Figure 10 decomposes real household income by income endowment in 2036. Wealthier households

[12]Figure 19 in Appendix B reports changes in real full consumption for the 1% scenario. Summing up a discounted stream of the absolute change in real full consumption approximates changes in equivalent variation closely.

[13]Research has shown that income effects tend to dominate welfare effects relative to effects from changes in final goods prices for analysis of environmental regulation (Marten, 2019).

Figure 7: Sectoral Output (LP Effect=1%)

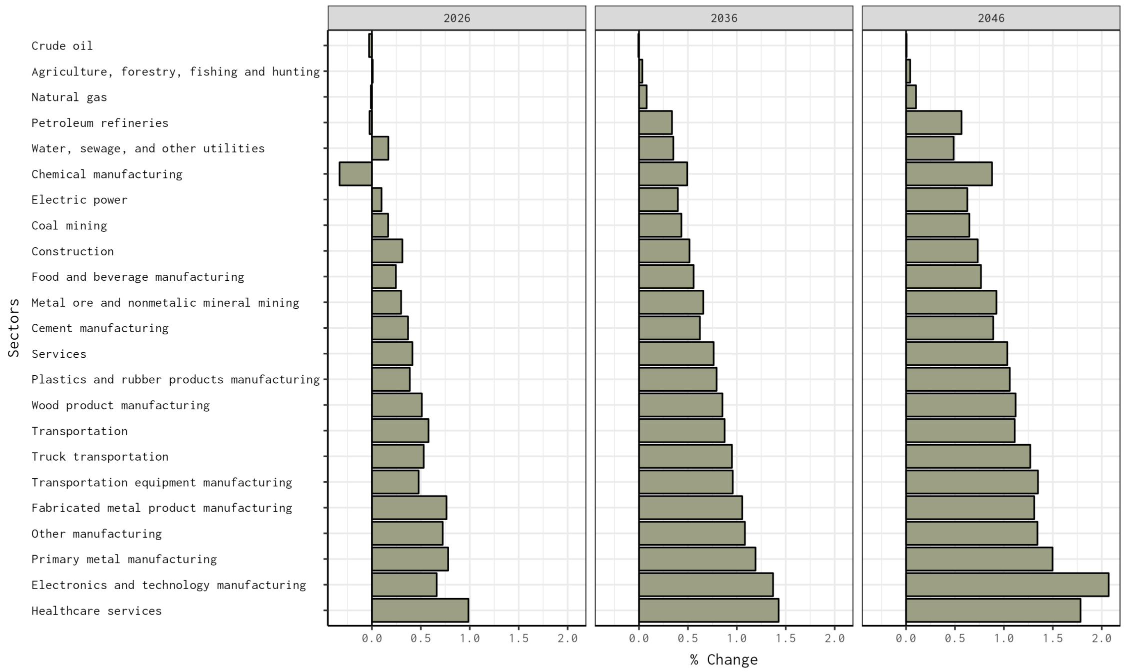
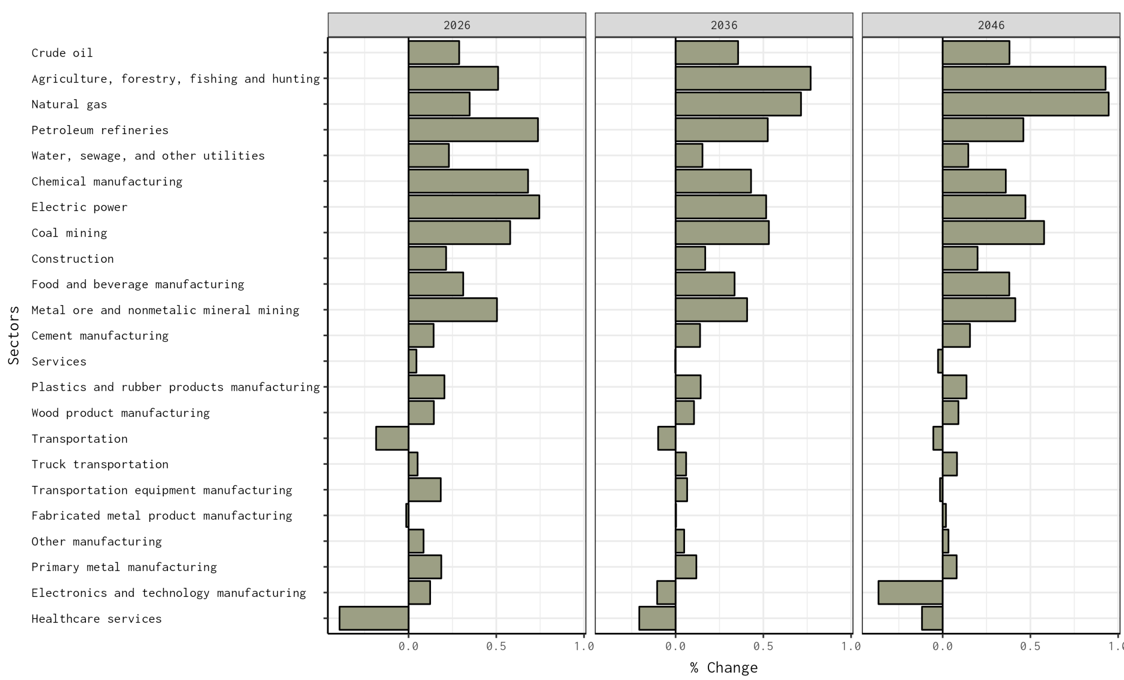
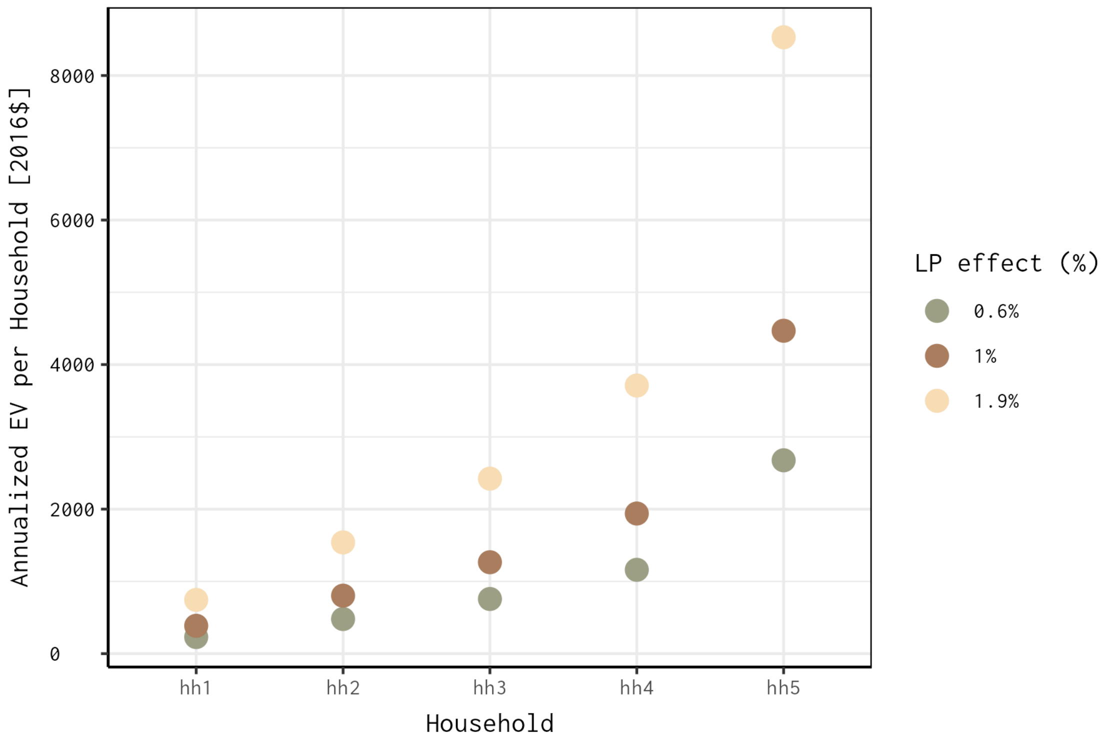


Figure 8: Sectoral Output Prices Relative to CPI (LP Effect=1%)



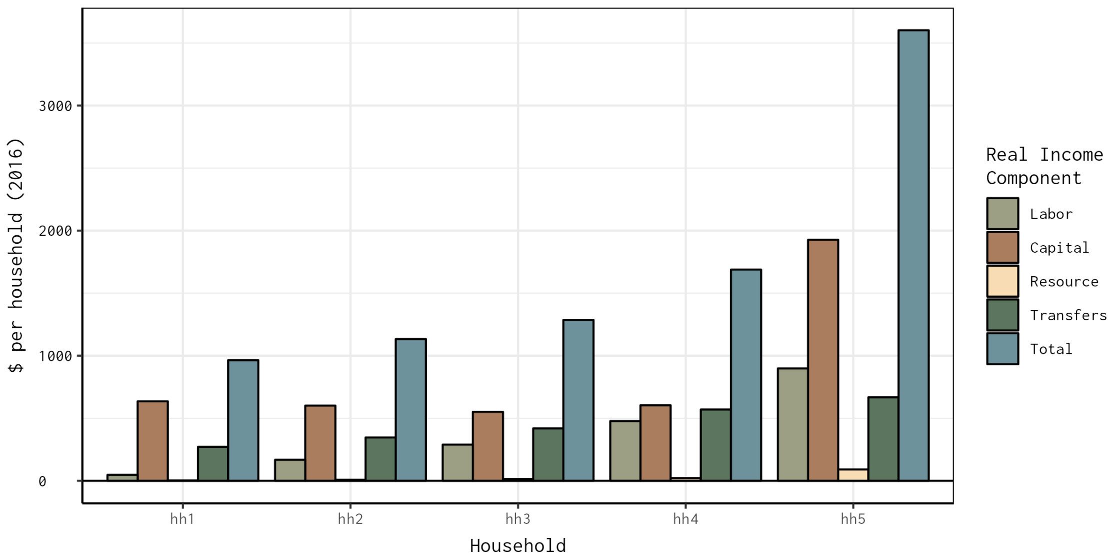
accrue relatively more absolute real income from changes to labor and capital income. Changes in transfer income occur through the government budget closure assumption in the model. Holding government expenditures fixed while the economy expands induces revenue recycling of additional government revenues back to households.[14]

Figure 9: Equivalent Variation By Household and LP Effect (4.5% discount rate)



[14]Figure 20 in Appendix B reports the aggregate change in real income and components over time for the 1% scenario. The relative change in components to real income shift over time as the model builds more capital and wage rates rise relative to the CPI.

Figure 10: Absolute Change in Real Income in 2036 by Household and Component (LP Effect=1%)



5.2 Modeling Heterogeneities

This section reports results from our Sector Differentiated and Occupational Frictions scenarios. We find that the aggregate welfare results are quite similar to the Core scenario results due to the shock sizes being calibrated to an equivalent economy-wide productivity effect.[15] Table 5 presents welfare results and we see that they are quite close - within 4% of the EV of the Core scenario. Both heterogeneity in the distribution of the input shock (Sector Differentiated) and heterogeneity in the inputs and model structure (Occupational Frictions) do not lead to large aggregate welfare differences. Marten et al. (2024b) find a similar outcome in their analysis of the costs of the 1990 Clean Air Act Amendments, finding that the additional labor market friction has limited overall welfare effects but can have a significant impact on the incidence of regulation. Similarly here, Table 5 masks variation in the composition of aggregate equivalent variation.[16]

Figure 11 reports annualized equivalent variation by household across the three modeling heterogeneity scenarios. While the Core and Sector Differentiated scenarios yield very similar results,

[15]We force the equivalency by calibrating a scale factor on the input shock. Let ϕ^c be the uniform labor productivity shock, ϕ^{sd}_{rs} be the sector differentiated shock that differs by sector (s) and region (r), ϕ^{of}_{o} be the occupational frictions shock indexed by occupation o, and $\overline{ld}_*$ be reference labor demands. For the sector differentiated shock, we calibrate a uniform scaling factor, γ, such that $\sum_{rs} \overline{ld}_{rs}(\phi^{sd}_{rs} + \gamma) = \phi^c \sum_{rs} \overline{ld}_{rs}$. Similarly for the occupational frictions scenario, we calibrate γ, such that $\sum_{rso} \overline{ld}_{rso}(\phi^{of}_{o} + \gamma) = \phi^c \sum_{rso} \overline{ld}_{rso}$.

[16]As a robustness check, we ran the occupational frictions model for the Core and Sector Differentiated scenarios and get almost identical welfare effects as the default version of the model.

Table 5: Welfare Impacts per Household by Model Heterogeneity

LP Effect (%)	**Annualized Equivalent Variation (EV,$)** *Core*	*Sector Differentiated*	*Occupational Frictions*	**EV % of Full Consumption** *Core*	*Sector Differentiated*	*Occupational Frictions*
0.6	946.9	911.3	921.6	0.6	0.6	0.6
1.0	1583.0	1524.4	1540.4	1.0	1.0	1.0
1.9	3028.7	2920.4	2946.1	1.9	1.8	1.8

Notes: Annualized per household EV is calculated assuming an infinite time horizon and annualized based on a 4.5% discount rate which is approximately the internal discount rate used in the SAGE model. All values are in 2016 dollars and discounted back to 2016.

the distributional variation in impacts is greater in the Occupational Frictions scenario. In this scenario, welfare benefits to lower income households are reduced, while benefits to the highest income household exceed those in other scenarios.

Figure 11: Equivalent Variation by Household and by Model Heterogeneity (LP Effect=1%, 4.5% discount rate)

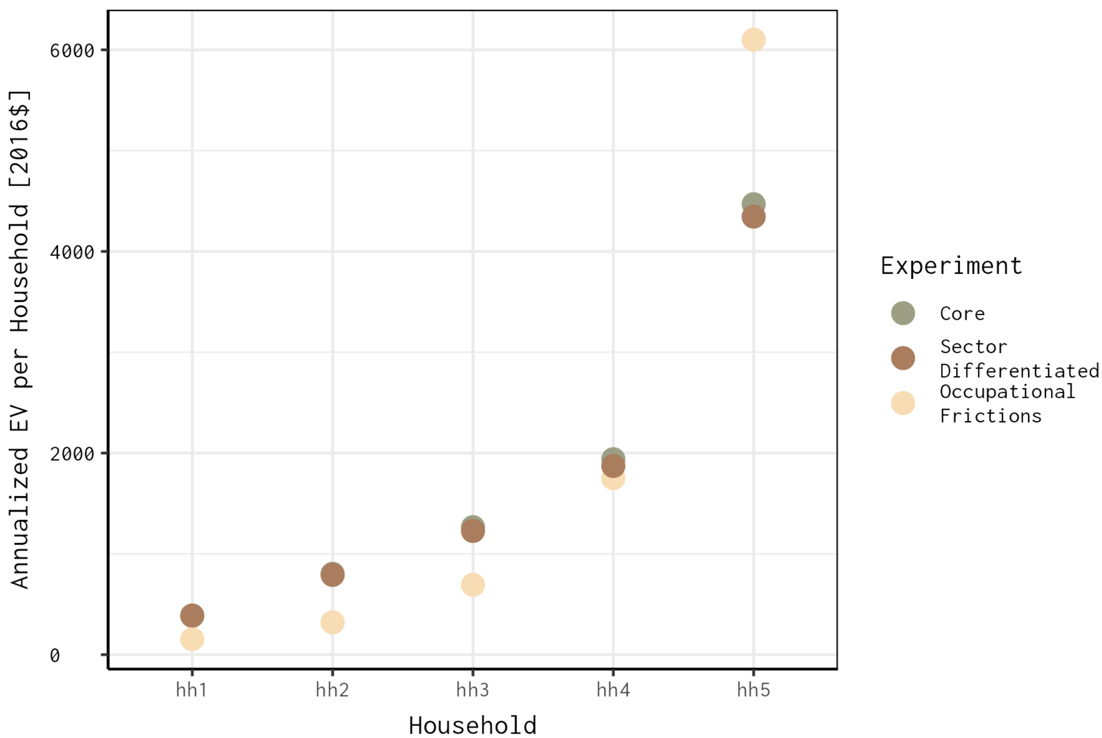


Figure 12 decomposes the effects shown in Figure 11 in the form of absolute changes in real income per household in 2036.[17] Components of income track each other quite closely in the Core and Sector

[17]Similarly, we report aggregate changes in real income over the time horizon in the model in Figure 21 in Appendix B.

Differentiated scenarios. In both cases labor productivity increases spur additional investment in the economy leading to growth in both labor income and capital income. In the Occupational Frictions scenario, the additional constraints on the substitutability between labor and capital induce a smaller investment response and relatively lower capital income growth (and even a negative capital income change for the highest income household).[18] Rather, rents accrue more so through the labor income channel to the highest income household group which is predominately composed of non-routine cognitive labor. In this scenario, the increase in productivity is heterogeneous across occupations. The augmented production function treats routine labor (getting the largest productivity increase) as substitutable with capital, and other occupation types as complements. Relatively more productive routine labor induces relatively less needed to produce output which shifts labor supply toward the more lucrative non-routine cognitive occupation. However, restrictions in the mobility between occupations on the supply and demand side of the model lead to relatively larger wage increases for non-routine cognitive workers.[19]

Figure 13 shows aggregate output by model scenario. We see that while the Core and Sector Differentiated scenarios track each other very closely, the occupational frictions model has somewhat lower aggregate production. The occupational model introduces more constraints on the ability for the model to both substitute between labor types in production and shift the supply of labor between occupations. These additional constraints lead to muted effects on the aggregate output margin in the model.[20]

[18] These series of effects are observable in Figure 22 which shows constituents of aggregate GDP by model scenario. Again the Core and Sector Differentiated scenarios track quite closely. We see however, that the Occupational Frictions model again diverges - investment in the Occupational Frictions model remains depressed relative to other scenarios.

[19] See Figures 23 and 24 in Appendix B that report labor supply and wage impacts across the scenario types.

[20] Figures 25 and 26 in Appendix B show sectoral output and price changes in 2036 by model heterogeneity. There are slight differences in the Core and Sector Differentiated scenarios based on which sectors have larger or smaller productivity shocks. The occupational frictions scenario yields smaller output changes due to structural constraints on the ability to substitute between different types of labor.

Figure 12: Absolute Change in Real Income in 2036 by Household and Component by Model Heterogeneity (LP Effect=1%)

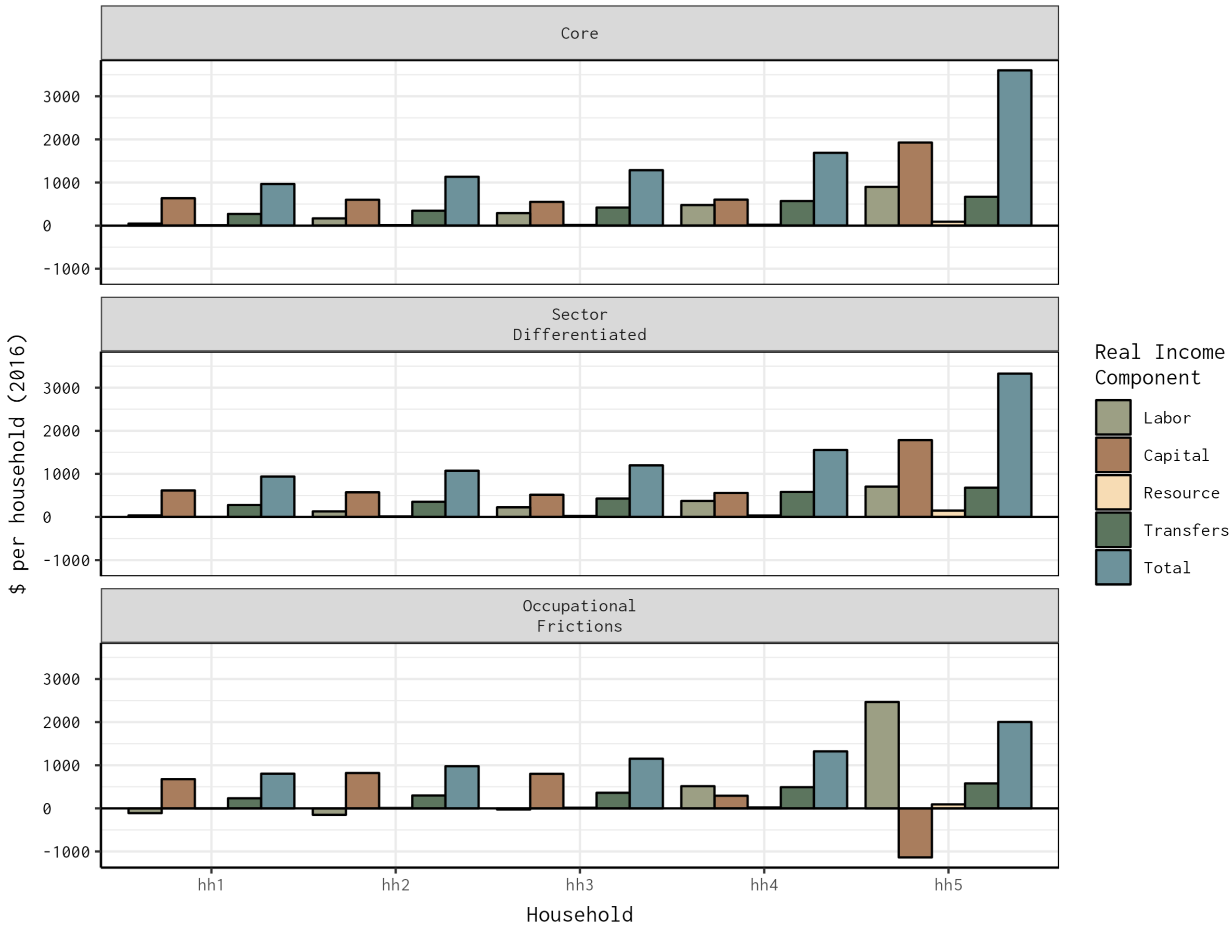
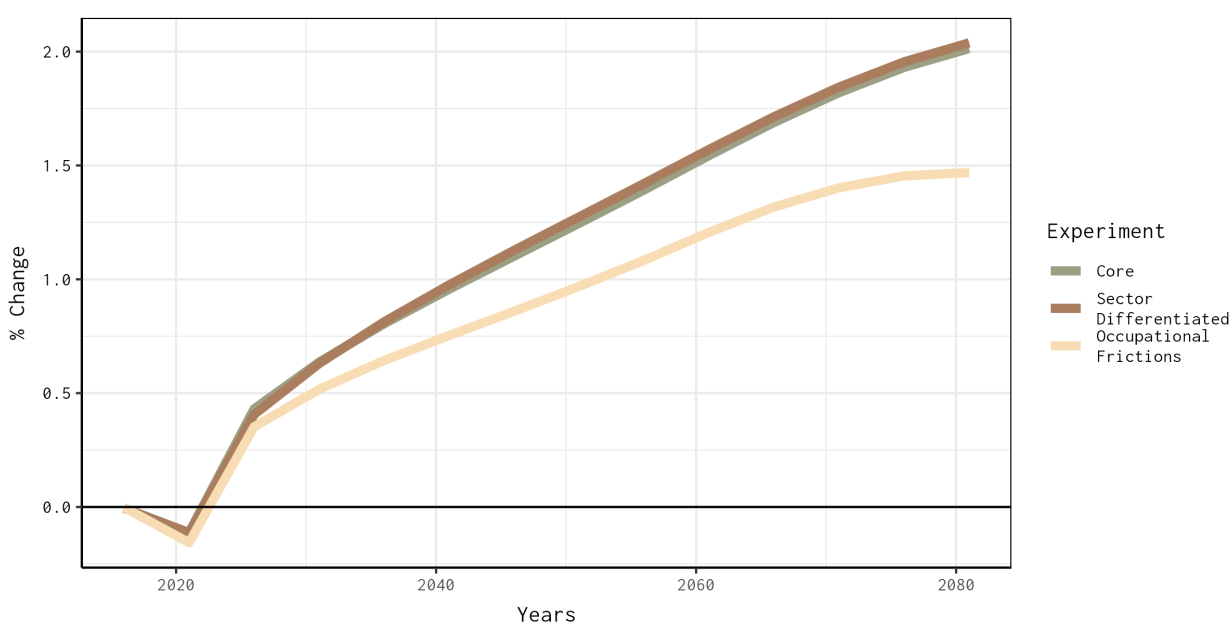


Figure 13: Aggregate Output by Model Heterogeneity (LP Effect=1%)

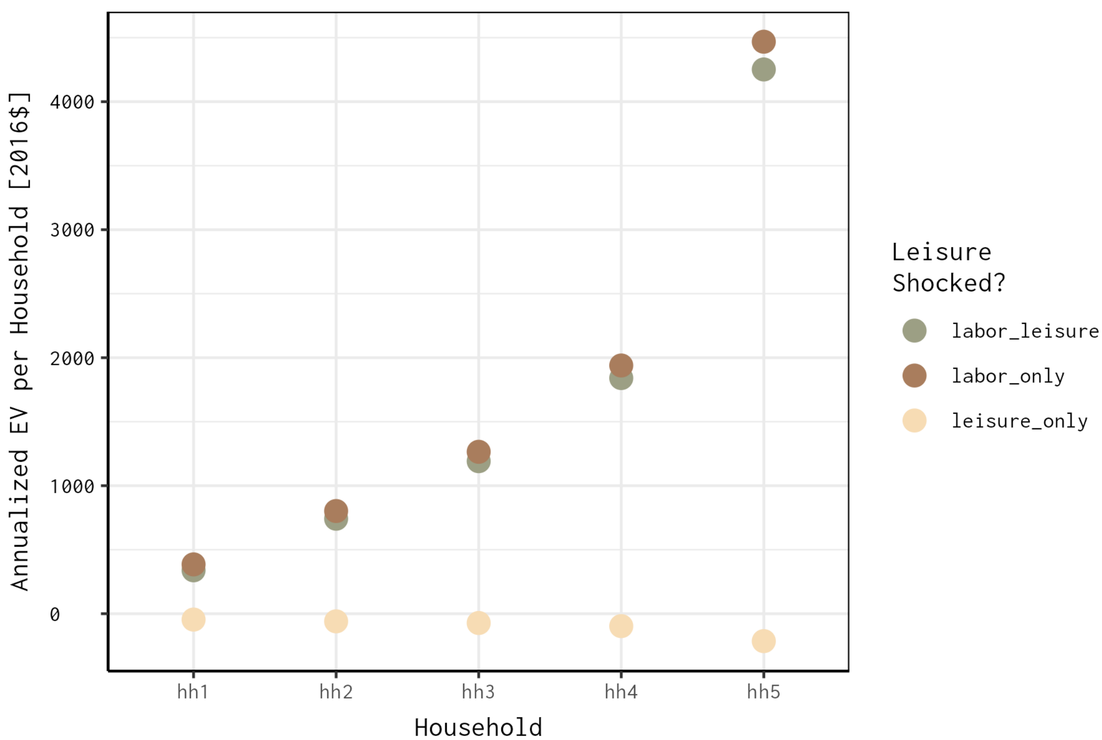


5.3 Labor-Leisure Choice

This section explores our results' sensitivity to modeling the effect of air pollution on leisure using the Core 1% scenario. In this section, we compare our Core results to a model with a commensurate shock to leisure productivity. We find that the effect of labor productivity on aggregate welfare is insensitive to modeling the effect of leisure productivity. However, shocking leisure productivity does change the labor-leisure tradeoff and does affect both labor supplied and aggregate consumption.

Figure 14 shows the equivalent variation by household for shocking labor and leisure, labor only, and leisure only. Shocking labor only produces very similar results to shocking labor and leisure, suggesting that the aggregate results are insensitive to the leisure shock. Shocking labor and leisure does produce benefits that are smaller in magnitude than shocking labor only. Similarly, shocking leisure only produces negative welfare benefits.

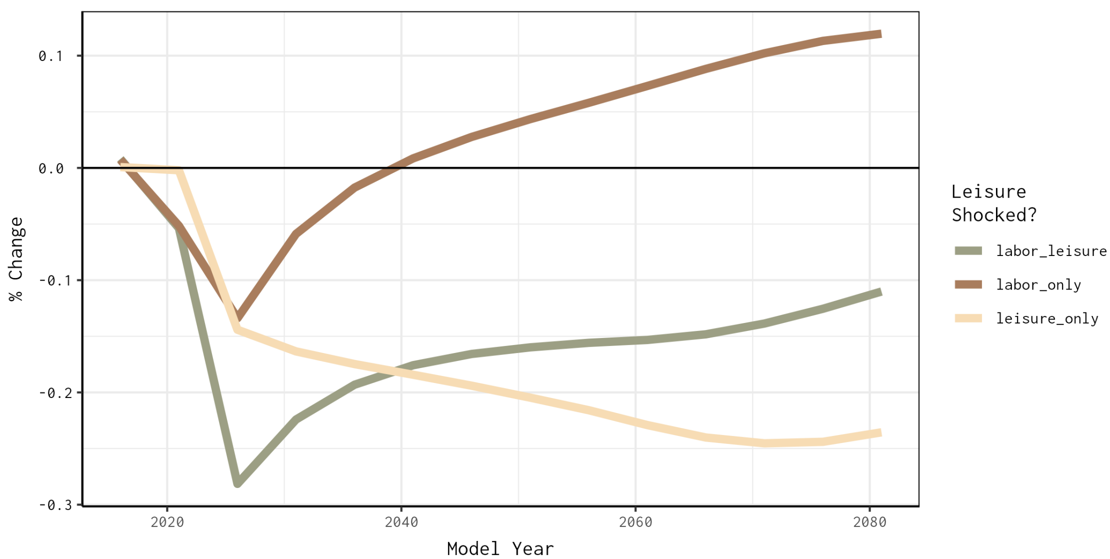
Figure 14: Equivalent Variation ($ per household per year) by Labor/Leisure Shock Assumption and Household Income (LP Effect=1%, 4.5% discount rate)



The shock to leisure operates in the same way as the shock to labor in sectoral output. It takes less leisure to produce the same amount of utility which notably, produces a net *negative* welfare effect. Two things are going on. Increasing the "productivity" of leisure has a direct effect of increasing utility. However, this induces an inward shift in the labor supply curve, yielding a reduction in labor supply (because leisure is more valuable). Given pre-existing distortions in the economy, the tax interaction effect propagates in the opposite direction as the utility gained from enjoying leisure more. A contracting labor force yields additional welfare reductions because it is an already distorted market. The latter effect dominates the former.[21] This effect, however, is small in comparison to the supply side of the model.

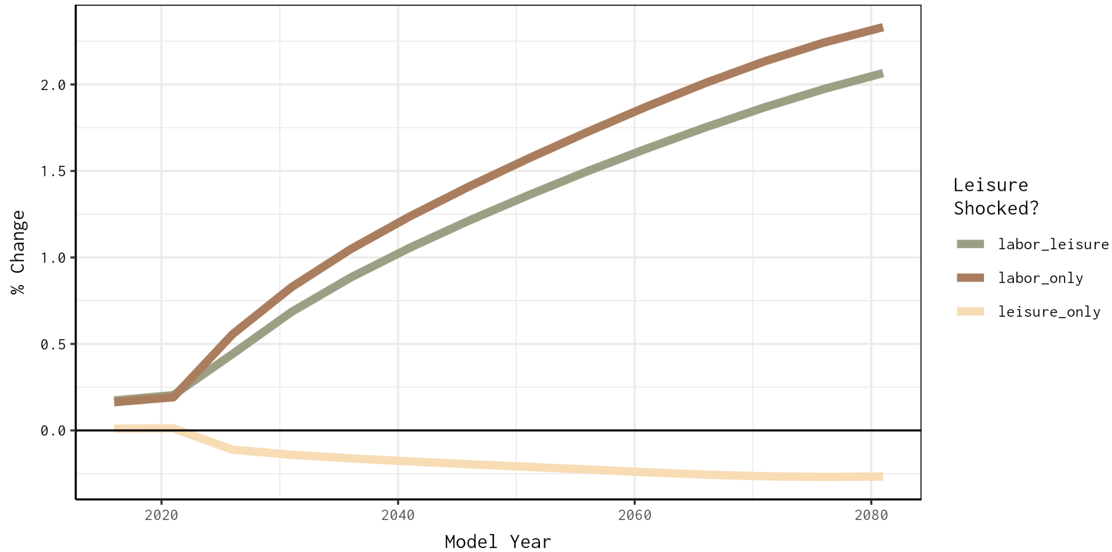
Figures 15 and 16 show the effect of the leisure shock on labor supply and consumption. When shocking leisure only, households reallocate consumption toward leisure demand which produces a downward effect on labor supply. Imposing a labor productivity and leisure shock simultaneously is approximately additive of the labor only and leisure only scenarios.

Figure 15: Change in Labor Supply by Labor/Leisure Shock Assumption (LP Effect=1%)



[21]This tax interaction effect can be confirmed using a simple version of SAGE (called BEIGE) with and without taxes. Shocking the simple model in an equivalent way for leisure increases welfare in a model without pre-existing distortions and decreases welfare in a model with existing distortions.

Figure 16: Change in Aggregate Consumption by Labor/Leisure Shock Assumption (LP Effect=1%)



6 Conclusion

This paper asks what are the welfare effects of air pollution's effect on labor productivity. We answer that question with a general equilibrium model. We use this model to estimate welfare impacts of labor productivity changes due to changes in air pollution. We document that labor market productivity changes associated with a one $\mu g/m^3$ reduction in $PM_{2.5}$ can have a large welfare impact, with welfare changes on the order of mortality impacts. Prior literature has been primarily econometric, generally using either detailed microdata studies of specific workplaces or aggregate measures of production. By working in general equilibrium, we are able to estimate welfare effects that are inclusive of interactions across the economy. For plausible parameterizations, the labor productivity impacts of air quality improvements translate into $950-3000 per household per year, which is roughly equivalent to 50-160% of the value of mortality risk reductions. For context, mortality risk reductions due to air quality improvements account for a majority of the monetized benefits of all federal regulations in recent years.[22]

We also find that adding model detail such as sectorally variable shocks or shocks to the value of leisure time has very little effect on aggregate welfare results. This model details do however have a substantial effect on detailed outcomes such as sectoral labor allocation.

[22] The most recent data available are from Tables 1-1 and 1-2 in OMB (OMB).

Several additional caveats remain. First, there remains uncertainty as to the average effect of $PM_{2.5}$ on labor productivity. As shown in Section 5.1, the welfare effects of labor productivity changes. are proportional to the changes. Second, there is substantial uncertainty in our measure of varying shocks. Our current measure implicitly assumes that exposure only happens while working outdoors, that it happens equally to different outdoor workers, and that our outdoors index accurately measures time spent working outdoors. We also assume that a reduction in $PM_{2.5}$ leads to the same labor productivity effect across locations and work contexts. The effect may vary with baseline conditions such as baseline exposures or health as well as type of work. Third, results from the CGE model are based on its default parameterization only. We have not tested the sensitivity of results to some assumed parameter values that may be important drivers of welfare changes (e.g., labor supply elasticities, k-l substitution elasticities). Fourth, this paper does not consider other effects of possible air quality changes such as the changes in compliance costs of regulations which might produce those changes. Fifth, the econometric results are based on short-term variation in air quality. Permanent shifts could lead to averting behavior, adaptation in work processes, and shifts in technology which could lead to different effects on labor productivity and different welfare impacts.

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A Calculating the Change in Mortality

Now let us compare the cost of a shock to labor productivity to the mortality impacts of an equivalent change in $PM_{2.5}$. We focus on mortality because mortality costs typically constitute about 90% of the monetized health benefits of air pollution changes. Using the U.S. EPA's BenMAP-CE tool, we estimate that a uniform one $\mu g/m^3$ reduction would lead to 17,698 fewer fatalities in 2026 and 27,179 fewer fatalities in 2046. These reductions correspond to benefits per household of $2,073 and $2,699 respectively. These average to $1,869 when discounted back to 2024 at a 2% rate.[23] The model years 2026 was chosen because it is the first year of the labor productivity shock. The model year 2046 was chosen because it is the last year of the labor productivity shock which is available in BenMAP-CE.

The EPA's BenMAP-CE tool calculates the health impacts of changes in air pollution. The user provides maps of air quality across the continental U.S. We used a map of specifying a constant ambient level of the average U.S. $PM_{2.5}$ level of 7.8 $\mu g/m^3$ and a map specifying a constant ambient level of 6.8 $\mu g/m^3$. BenMAP-CE then calculates the difference in exposure for 12x12 km grid cells across the United States and multiplies by a baseline incidence rate and a slope coefficient relating the change in $PM_{2.5}$ to a percentage change in outcomes. This is described in Equation 3

$$\Delta M_y = \sum_a \sum_i \Delta PM_{2.5} * \eta_a * M_i^0 ya \tag{3}$$

In Equation 3, ΔM_y describes the national change in mortality in the year y as a count. This is the sum across all grid cells i and all demographic groups a of the product of $\Delta PM_{2.5}$ which describes the change in $PM_{2.5}$, $M_i^0 ya$ which describes the baseline mortality in grid cell i in year y, and η_a which describes the percent change in mortality per change in $PM_{2.5}$. BenMAP-CE currently supports differentiating demographic groups by age. For mortality, the we use adults ages 30 and up. We use the Turner et al. (2016) estimate of the effect of $PM_{2.5}$ on mortality. We used BenMAP-CE version 1.5.8.33.

[23] BenMAP-CE reports changes in incidence, exposed population, and valuation. We divide the exposed population by 3.15 to estimate the number of households.

B Additional Results

This section includes additional results beyond those listed in Section 5 as a reference for the interested reader.

B.1 Additional Results from Core Scenario

Figure 17: Terms of Trade Impacts: % Change in Ratio of Export to Import Price (LP Effect=1%)

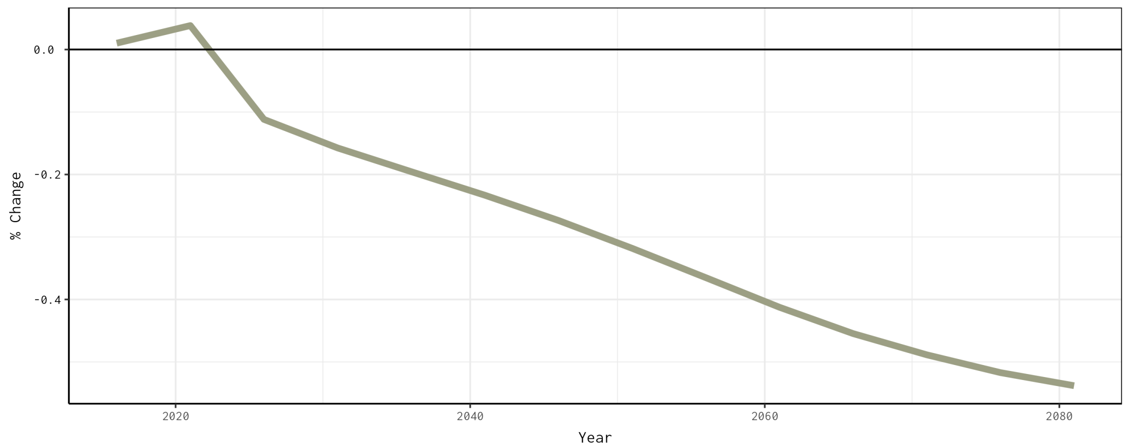


Figure 18: Consumer Price Index (CPI) Relative to the Price of Foreign Exchange (LP Effect=1%)

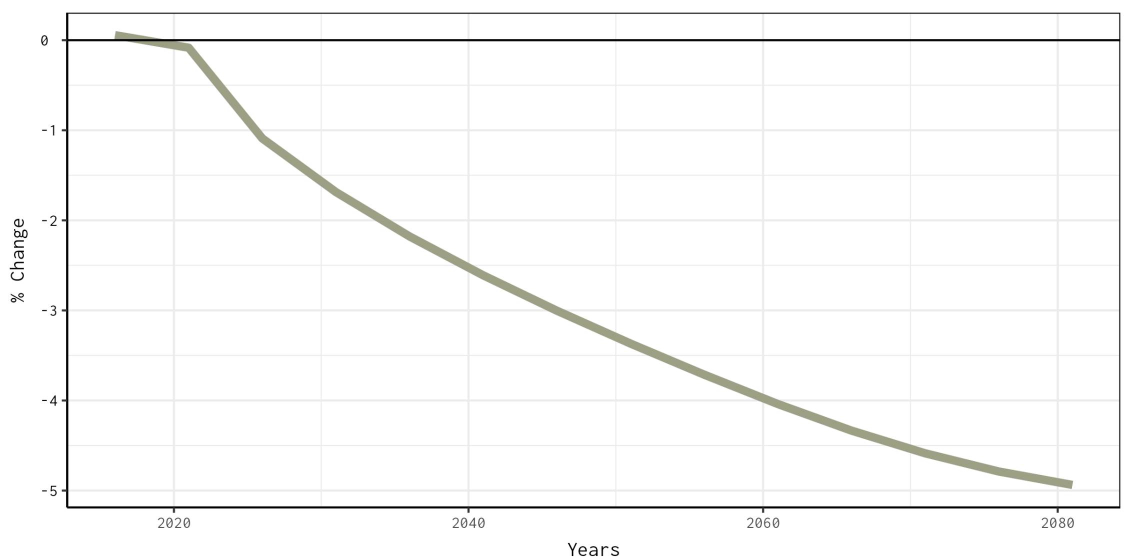


Figure 19: Real Full Consumption by Household (LP Effect=1%)

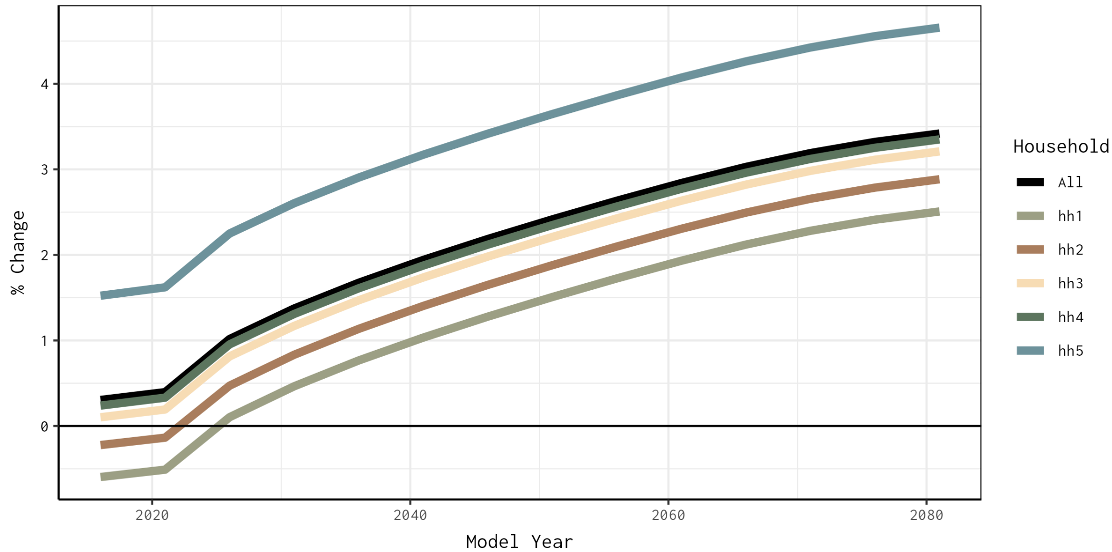
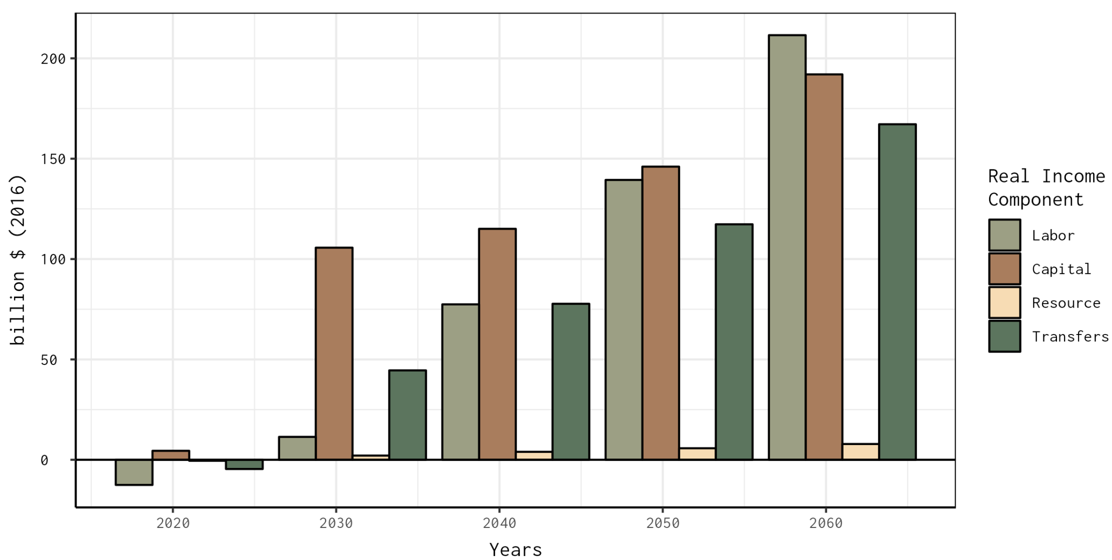


Figure 20: Absolute Change in Real Income Over Time by Component (LP Effect=1%)



B.2 Additional Results from Heterogeneity Models

Figure 21: Absolute Change in Real Income Over Time by Component by Model Heterogeneity (LP Effect=1%)

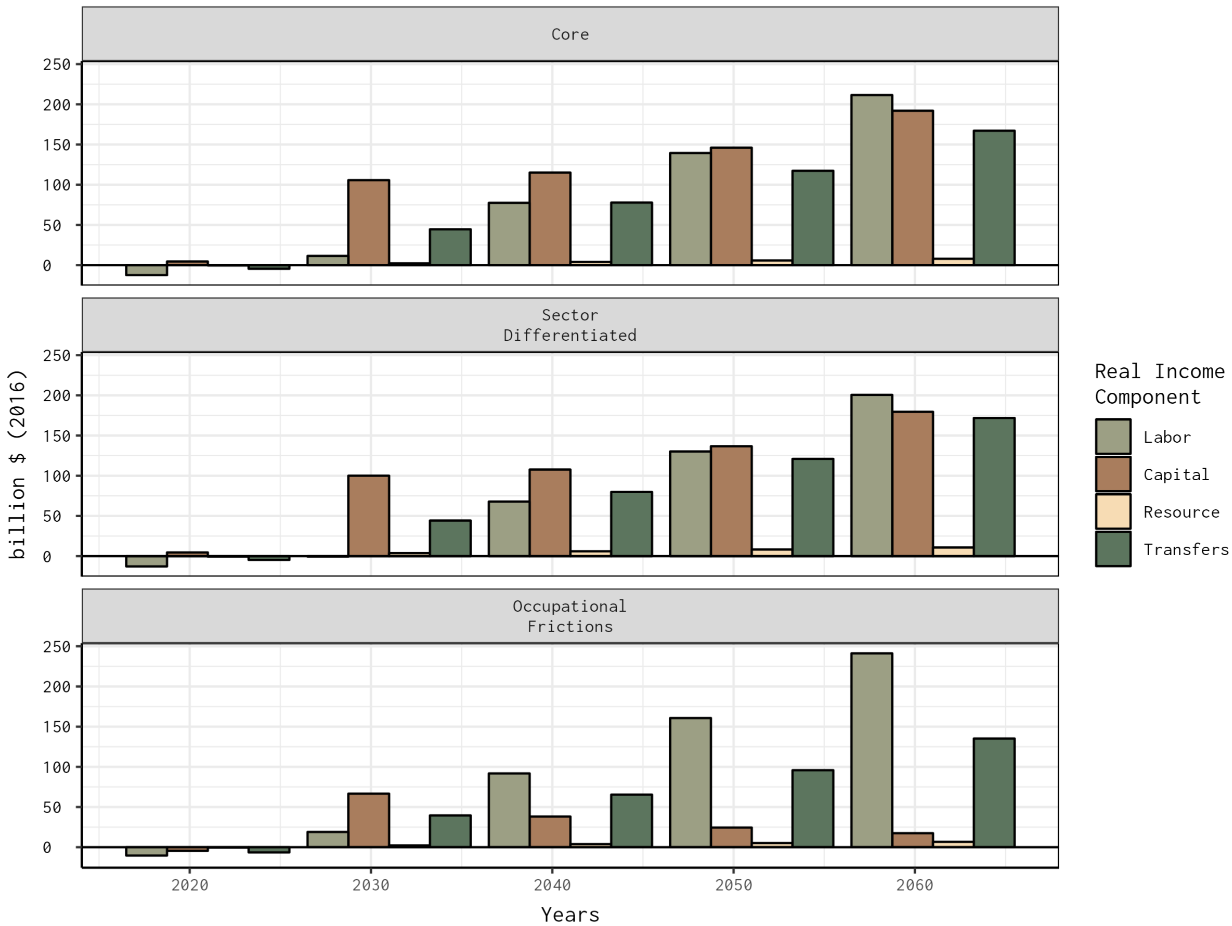


Figure 22: GDP and its Components by Model Heterogeneity (LP Effect=1%)

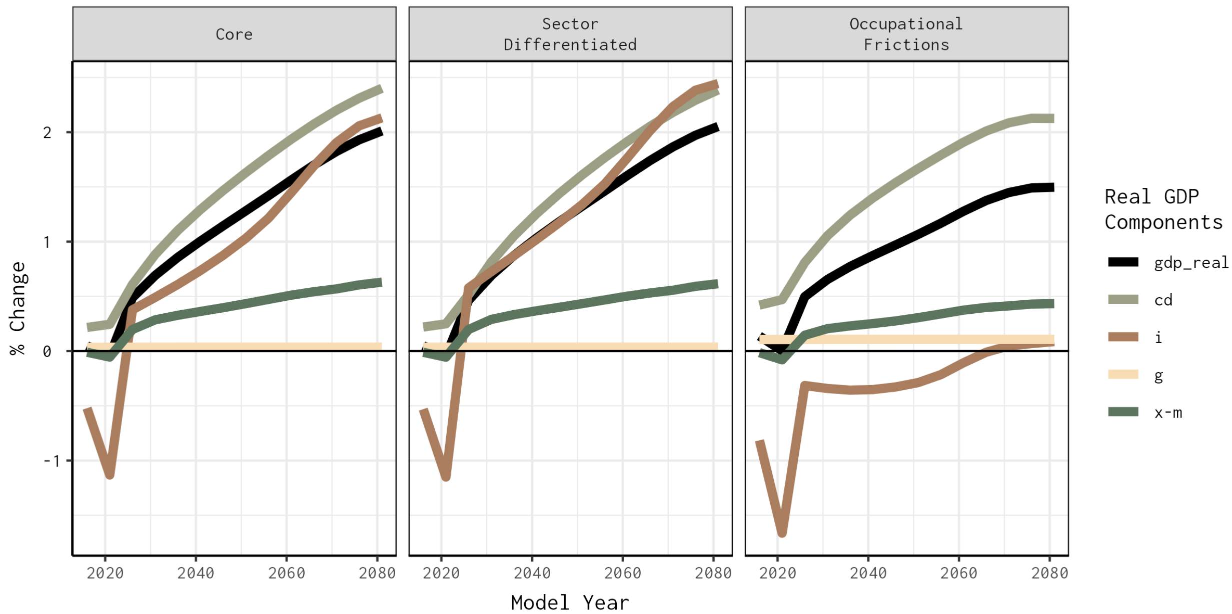
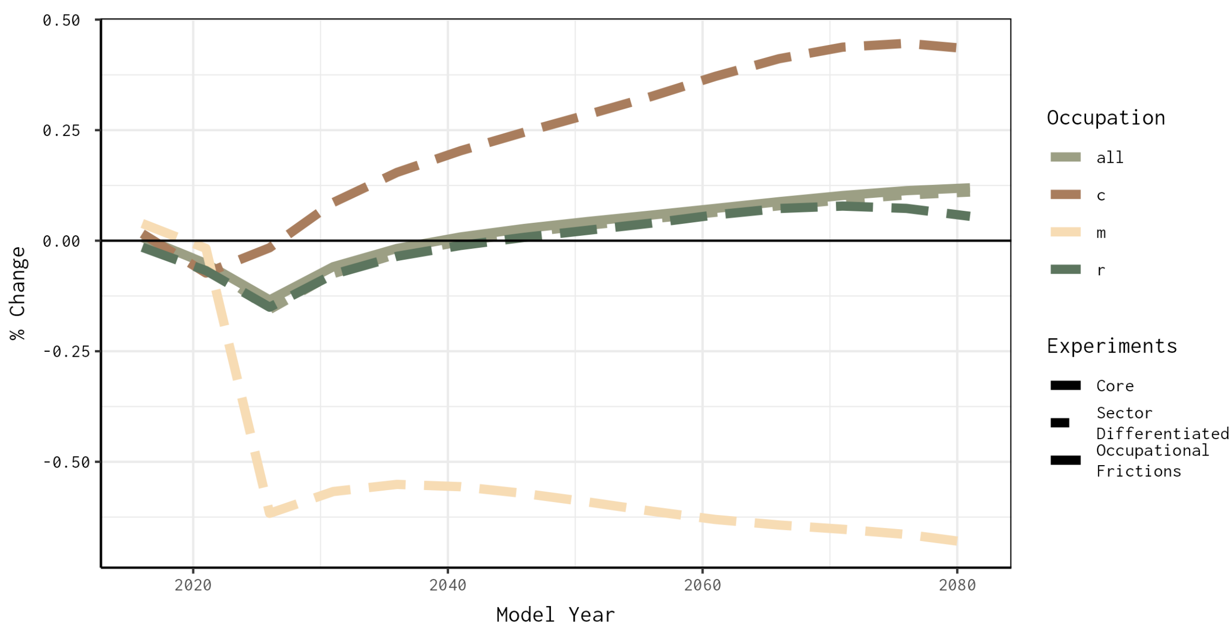


Figure 23: Labor Supply Impact by Model Heterogeneity (LP Effect=1%)



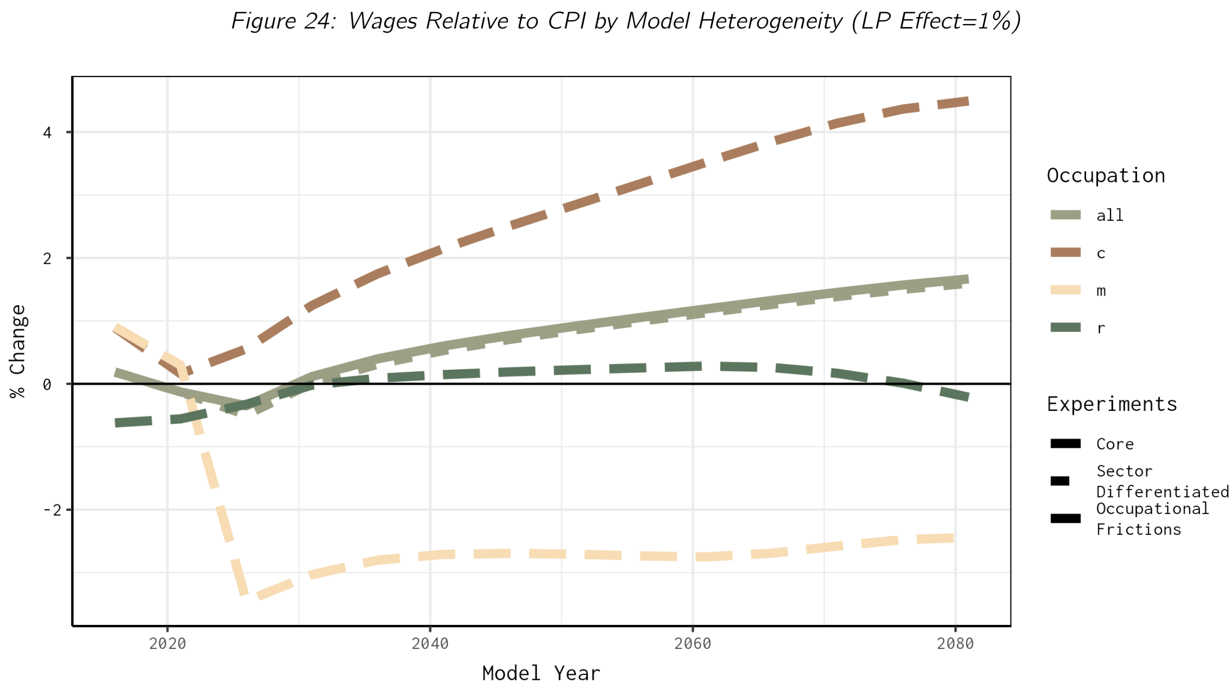


Figure 24: Wages Relative to CPI by Model Heterogeneity (LP Effect=1%)
% Change
Model Year
4
2
0
-2
2020
2040
2060
2080
Occupation
all
c
m
r
Experiments
Core
Sector Differentiated
Occupational Frictions

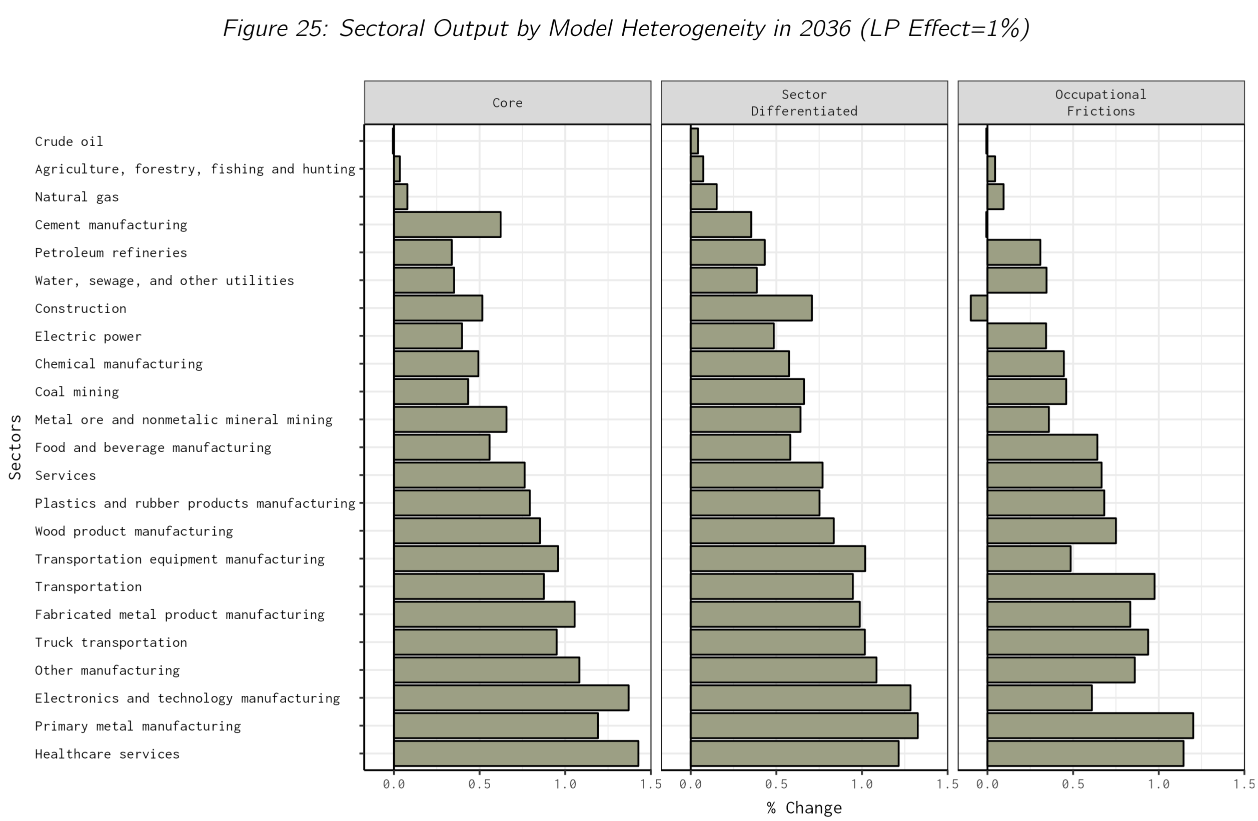


Figure 25: Sectoral Output by Model Heterogeneity in 2036 (LP Effect=1%)
Core
Sector Differentiated
Occupational Frictions
Sectors
Crude oil
Agriculture, forestry, fishing and hunting
Natural gas
Cement manufacturing
Petroleum refineries
Water, sewage, and other utilities
Construction
Electric power
Chemical manufacturing
Coal mining
Metal ore and nonmetalic mineral mining
Food and beverage manufacturing
Services
Plastics and rubber products manufacturing
Wood product manufacturing
Transportation equipment manufacturing
Transportation
Fabricated metal product manufacturing
Truck transportation
Other manufacturing
Electronics and technology manufacturing
Primary metal manufacturing
Healthcare services
0.0
0.5
1.0
1.5
% Change

Figure 26: Sectoral Output Prices Relative to CPI by Model Heterogeneity in 2036 (LP Effect=1%)