Shifting Tastes, Advancing Technologies: A New Perspective on Income Inequality

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Rising income inequality has been a defining feature of developed economies since the 1980s, with technological change widely cited as a key driver. Yet, this narrative overlooks another fundamental transformation: the dramatic evolution in how consumers spend their money. This paper shows that changing consumer demand has played a crucial role in moderating income inequality in the US over the period 1989-2021. Using a novel framework that separates demand changes from price and income effects, I demonstrate that shifts in consumption patterns have benefited workers in service-oriented sectors that have traditionally been viewed as less productive, particularly those working in routine cognitive and non-routine manual jobs. Without these demand changes, the rise in income inequality would have been 73% larger. These shifts in consumer spending resulted in a reallocation of economic activity toward sectors with lower productivity growth – a pattern consistent with Baumol's cost disease. These changes are associated with more equitable income distribution, suggesting that the demand-driven slowdown in productivity growth may be associated with a trade-off between growth and equity.

JEL: E21, E24, L16, O33
Keywords: Income Inequality, Consumer Demand, Nonhomothetic CES Preferences, Demand Growth Factors, Changing Demand, Technological Change, Structural Change

1 Introduction

Over the past four decades, developed economies have experienced two profound transformations: a dramatic rise in income inequality and a substantial shift in consumption patters (Saez and Zucman, 2020; Piketty et al., 2018). In the US, demand for various services has surged. Household maintenance spending has increased eight-fold. Expenditures of health insurance are now ten times higher than in the 1990s. Recent research has shown that technological change drives inequality by primarily benefitting skilled and non-routine workers (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022). Yet, little attention has been given to the effects of shifting consumer demand on income distribution. As consumer spending is redirected across sectors, so too does labour demand, potentially reshaping the distribution of wages. This paper addresses this gap by exploring a fundamental question: How do changes in consumer demand affect income inequality?

This paper makes several key contributions to the literature. First, I develop a novel general equilibrium structural transformation model that captures changes in demand through time-varying demand shifters, which I refer to as Demand Growth Factors (DGFs). These demand shifters operate independently from traditional price and income effects. Second, using the estimates from the proposed framework, I document significant changes in consumer demand over the period 1989-2021 and show that these changes are heterogeneous across different household and good types. Third, I demonstrate that DGFs-driven demand changes have a substantial impact on wages and income inequality, with demand changes often counteracting the deleterious effect that technological change has on income inequality. In the absence of changes in demand, the increase in income inequality, captured by the coefficient of variation (CV), would have been 73% greater. Changes in demand have particularly benefitted workers in service-oriented sectors that have traditionally been viewed as less productive.

The existing literature has largely focused on supply-side explanations for rising inequality. A significant body of work has identified skill-biased technological change as a primary contributor, demonstrating how technological advancements have disproportionately benefited highly skilled workers (Katz and Murphy, 1992; Autor et al., 2003). Building on this foundation, more recent studies have highlighted the impact of routine-biased technological change, which has led to job polarization and further wage disparities (Goos et al., 2014; Autor and Dorn, 2013). While this literature has greatly advanced our understanding of supply-side drivers of inequality, it has paid less attention to how evolving consumer demand could independently influence distributional outcomes.

Recent work on structural change highlights the importance of considering demand-side factors in understanding economic outcomes. The canonical structural transformation model, used by Buera et al. (2022); Comin et al. (2021); Boppart (2014); Herrendorf et al. (2013); Buera and Kaboski (2012); Ngai and Pissarides (2007), among others, employs non-homothetic preferences to examine how changes in sectoral composition arise from the demand side through income effects and relative prices. However, even in these demand-focused models, changes in consumption patterns are still ultimately governed by production-side factors, since both income and relative prices are determined by production. In the absence of changes in income or relative prices, the consumption structure in these models remains stable over time. Thus, these models may not fully capture the potential effects of evolving consumer demand on structural change and income inequality.

In this paper, I extend this model by introducing time-varying demand growth factors, DGFs. In the model, DGFs capture evolving consumer demand that is independent of price and income effects. They can account for unobservable changes in product quality due to technological advancements (Syverson, 2017), as well as taste shocks that affect spending allocations (Baqaee and Burstein, 2023). These factors, often overlooked in traditional models, can significantly affect spending patterns in ways not captured by price or income adjustments alone.

In the model, preferences are heterogeneous across four households – non-routine cognitive, routine cognitive, non-routine manual, and routine manual.[1] Each household consumes four goods, with each good produced by one of the four sectors – non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), non-routine manual intensive (NMI), and routine manual intensive (RMI).[2] This sectoral classification departs from the traditional agriculture-manufacturing-services framework, allowing me to capture important heterogeneity within the rapidly expanding services sector. Technological change is captured by a CRESH production function with factor-augmenting technical growth rates, building on similar CES production function specifications by Herrendorf et al. (2015) and León-Ledesma et al. (2010). This specification allows for different elasticities of substitution between input pairs, providing greater flexibility in modelling production technologies across sectors.

To estimate the model and perform counterfactual analysis, I link quarterly household-level expenditures from the Consumer Expenditure Survey (CEX) data for the US over the period 1989-2021 to sectoral production data through a series of mappings and aggregations. I do this using Input-Output Tables, Integrated Industry-Level Production

[1] I split households into four types – non-routine cognitive, routine cognitive, non-routine manual, and routine manual, based on the occupation of the reference person. Occupation type is determined based on O*NET task measures, following Acemoglu and Autor (2011). For more discussion, see Section 2 and Appendix B.

[2] Sector types are determined based on relative labour type shares, as discussed in Section 2 and Appendix B.

Accounts (KLEMS), Current Population Survey (CPS), and the Occupational Information Network (O*NET) data. Expenditure data is aggregated at the level of four households. The labour employed by each sector is divided into four occupation groups. The four occupation groups are the same as the four types of households (NCI, RCI, NMI, and RMI). This dataset allows me to analyze the interplay between changing consumer demand and production technologies in a general equilibrium setting.

The results of this paper provide new insights into the dynamics of income inequality and structural change. I find that DGFs play an important role in shaping wage distributions across sectors and households. Specifically, changes in demand have particularly benefited workers in service-oriented sectors that are traditionally viewed as less productive, particularly those in non-routine manual intensive and routine cognitive intensive sectors. DGF effects partially offset negative production effects for households employed in these sectors. The magnitude of these effects is substantial: in the counterfactual scenario without demand effects, wages[3] in 2021 in the routine cognitive intensive sector are 10% lower, while wages in the non-routine manual intensive sector are 15% lower. Conversely, wages in the routine manual intensive sector are 25% higher in the absence of demand effects. These wage effects underscore the importance of changing demand in shaping income distributions.

In the absence of demand effects, income inequality, measured by the CV, would have increased by 73% more between 1989 and 2021. To understand the economic significance of these demand effects, I compare them to a benchmark scenario with neither demand nor technological change effects. The results show that production effects alone would increase the CV by 0.086 relative to the benchmark, while demand effects alone would decrease the CV by 0.081. The magnitude of changes in income inequality due to demand effects is over 94% of that of production effects, but in the opposite direction. These findings suggest that evolving consumer demand has played a crucial role in moderating the rise of income inequality over the past three decades, largely counterbalancing the inequality-increasing effects of technological change. The results complement much of the existing literature that focuses primarily on technological change as the driver of inequality (e.g., Acemoglu and Restrepo (2022)) and highlight the pivotal role of demand-side factors.

I find that up to 20% of the DGF-driven wage effects arise from changes in household composition over time, particularly due to an increase in the share of higher-income non-routine cognitive households. As the share of non-routine cognitive households increases, so do the demand effects that counteract negative production effects on income inequal-

[3]CEX contains data on annual labour earnings/salaries. To match this, I also use annual labour earnings/salaries data from the CPS. In the paper, I refer to annual labour earnings or salaries as wages or income and use these terms interchangeably.

ity. This phenomenon creates a counterintuitive dynamic, where rather than inequality begetting more inequality, the changing composition towards higher-income households helps to temper income disparities through demand effects. Income inequality, to an extent, appears to be self-moderating. This result adds a new dimension to our understanding of structural change, complementing work by Buera et al. (2022) on skill-biased structural change by showing how evolving demand patterns interact with changing skill composition.

The results also provide a new perspective on Baumol's cost disease (Baumol, 1967). Consistent with Baumol's theory, I find that changes in demand increase economic activity in sectors with lower productivity growth and higher labour intensities, particularly routine cognitive intensive and non-routine manual intensive sectors. Although this shift may contribute to slower aggregate productivity growth, it is associated with more equitable income distribution. This suggests an important trade-off between productivity growth and equity that has been overlooked in traditional interpretations of Baumol's cost disease. These findings have important implications for our understanding of the relationship between structural change, productivity growth, and income inequality in developed economies.

The remainder of the paper is organized as follows. Section 2 presents data and key stylized facts on consumption patterns and income inequality. Section 3 develops the theoretical framework, introducing DGFs and integrating them into a general equilibrium model with technological change. Section 4 describes the estimation strategy and sources of identification for the parameters governing households' and sectors' choices in equilibrium. Section 5 presents estimation results for the households' and sectors' problems and demonstrates the superior performance of the proposed model with DGFs compared to the canonical model with non-homothetic CES preferences. Section 6 conducts counterfactual analyses to quantify the relative importance of demand effects on wages and wage distributions. Section 7 examines channels of DGF effects and performs robustness checks. Section 8 explores the implications of DGF-driven structural change for income inequality and its relevance for Baumol's cost disease and slowing economic growth. Finally, Section 9 concludes.

2 Data and Stylized Facts

The analysis in this paper is based on a dataset that maps household-level expenditure data to costs of labour and capital employed in the production of the goods and services consumed by households.[4] The dataset builds on the quarterly data from the Consumer Expenditure Survey (CEX) for the US over the period of 1989-2021 and is constructed through a series of mappings and aggregations, drawing from multiple data sources. First, I aggregate detailed expenditures from the CEX into Personal Consumption Expenditure (PCE) categories and then map them to National Income and Product Accounts (NIPA) expenditure lines. These are converted to commodity codes using PCE Bridge tables and then mapped to industry value added using Input-Output Tables. I then allocate industry value added to labour and capital using Integrated Industry-Level Production Accounts (KLEMS) data. These data preparation steps are similar to those in Buera et al. (2022), except that I further disaggregate industry labour costs to the level of occupations using data from the Merged Outgoing Rotation Group (MORG) from the Current Population Survey (CPS) data. Finally, I group occupations into four types – non-routine cognitive, routine cognitive, non-routine manual, and routine manual, using O*NET data. A detailed description of the data construction process is provided in Appendix B.

An important feature of the framework in this paper and the data is the classification of labour based on tasks. Following Acemoglu and Autor (2011), I construct four occupation-specific task intensity measures using O*NET data – non-routine cognitive, routine cognitive, non-routine manual, and routine manual task intensity measures. The type of occupation is determined by the largest task intensity. The data covers 420 occupations, and each labour type includes a wide variety of occupations by skill and education level. There are 139 non-routine cognitive occupations (e.g., computer programmers, funeral directors, and advertising sales agents), 82 routine cognitive occupations (e.g., paralegals, mapping technicians, and cashiers), 107 non-routine manual occupations (e.g., avionic technicians, paramedics, and carpenters), and 92 routine manual occupations (e.g., radiation therapists, railroad conductors, and postal service mail sorters).

I categorize industries as non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), non-routine manual intensive (NMI), and routine manual intensive (RMI) based on the composition of occupations within the industry. The top 25% of industries with the largest value added share of a specific labour type are determined to be intensive in that type.[5] Thus, this industry classification groups industries based on the intensity

[4] Consumption and expenditures are not necessarily the same. For simplicity, I use these terms interchangeably throughout the paper.

[5] I begin by classifying an industry as a specific type, if it's use of that type of labour, and only that type of labour, is within the top 25% of industries. For industries whose use of two types of labour is in the top 25% of all industries, the type was determined based on the relatively larger labour share. For more detail, see Appendix B. Table B.3 lists main industries by their type.

of their use of a particular labour type relative to other industries. Good types are determined by the type of industry that produces the good.[6] Finally, I aggregate all industries of the same type into a sector of that type. Thus, in the constructed dataset, households consume four goods produced by the NCI, RCI, NMI, and RMI sectors.

The definition of sectors in this paper differs from the standard sector definition in the structural transformation literature. Traditional approaches divide the economy into agriculture, manufacturing, and services sectors, whereas this paper defines sectors based on the nature of work, captured by task intensities. Such sector classification is particularly important for understanding the dynamics related to the services sector, where there is substantial heterogeneity in task content that is not captured by traditional sectoral aggregation. The services sector encompasses a wide variety of services, such as non-routine manual intensive landscape design and installation, non-routine cognitive intensive education services, and routine cognitive intensive insurance services. From the industries that comprise the services sector, 41% are non-routine cognitive intensive, 46% are routine cognitive intensive, and 13% are non-routine manual intensive.[7] The demand for different services evolves differently over time. If these trends in demand move in different directions, then grouping all services together would lead to a loss of important variation, masking important dynamics in structural transformation. A more detailed services classification is especially crucial given the well-documented shift towards services in developed economies (Herrendorf et al., 2013; Buera and Kaboski, 2012).

I calculate the price of each of the four goods as a weighted average of price indexes of PCE categories that comprise the good type, using PCE expenditures as weights, taken from NIPA Tables 2.4.4U and Table 2.4.5U, provided by the BEA.[8] While the expenditure data from the CEX is at the quarter-year level, all production data is at the annual level to match annual I-O Tables, KLEMS, and CPS data. Capital prices are obtained from capital expenditures and capital quantity indexes in KLEMS data, and wages for each

[6] Based on I-O Tables, final goods can be produced by multiple industries. To determine a good's type, I focus on the good's main industry – i.e., the industry that produces the largest share of the good's value added. I refer to this industry as the primary industry. For example, the production of women's and girls' clothing involves a number of industries, including the is produced by many industries, including the apparel and leather and allied products industry, the machinery industry, and the farms industry. The apparel and leather and allied products industry has the largest value added share in the production of women's and girls' clothing compared to others. Thus, I define it to be the primary industry for women's and girls' clothing. Table B.4 lists NIPA expenditure lines by their type.

[7] Table B.5 lists industries and their types for agriculture, manufacturing, and services sectors. Both manufacturing and services sectors have multiple industry types comprising these sectors. The services sector is particularly heterogeneous.

[8] NIPA BEA Table 2.4.4U. Price Indexes for Personal Consumption Expenditures by Type of Product `https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=underlying`. Table 2.4.5U. Personal Consumption Expenditures by Type of Product `https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=underlying`.

labour type are taken as salaries from the MORG CPS.

The sample includes 685,252 observations and is restricted to households with a reference person aged 25-65 with a non-missing occupation. The analysis excludes the top 1% and bottom 1% of households for each year based on total household salary. I split households in the CEX into four types to match labour types in the production data. Table B.1 reports summary statistics by household type.

I aggregate households from the CEX data into four households – non-routine cognitive, routine cognitive, non-routine manual, and routine manual households for each quarter using weights provided by the BLS that map CEX households into the national population.[9,10] Similarly, I aggregate expenditures into expenditures on the four goods – NCI, RCI, NMI, and RMI. This dataset contains expenditures on the four goods for the four aggregate households over the period from 1989 to 2021 at the quarterly level, resulting in 528 observations. The expenditures on the four goods –NCI, RCI, NMI, and RMI – are allocated to capital and four types of labour employed in the four sectors of the same type as the good the sector produces, resulting in 528 observations. I use this dataset for all analyses in the paper.

Figure 1 shows substantial heterogeneity in the evolution of expenditure shares and price dynamics across goods over the period 1989-2021.[11] The expenditure share of the RCI good increased the most over 1989-2021, followed by the expenditure share of the NMI good. The price of the RCI good also increased notably over the years. Conversely, the expenditure share of the RMI good decreased by almost 10 p.p. The expenditure share of the NCI good remained fairly stable over time. In 2021, expenditures on the RCI and NMI goods more than tripled compared to 1989 (see Figure B.7). Changes in consumption structure are also heterogeneous across households (see Figure A.1). The observed changes in expenditure shares and prices across different good types provide preliminary evidence for the potential role of evolving consumer demand in shaping income inequality.

Changes in expenditures on the RCI good are driven by a sharp increase in expenditures on health insurance, as well as rising expenditures on telecommunication services, audio and video services, paramedical services, group housing, and sales of used vehicles. In 2021, households spent almost 10 times more on health insurance compared to 1989. Changes in expenditures on the NMI good come from an increase in expenditures on transportation, as well as household maintenance, particularly in recent years.

[9] Prior to aggregating the expenditure data, I adjust the BLS provided weights based on the number of months in scope, following CEX representative population weights methodology: https://www.bls.gov/cex/pumd-getting-started-guide.htm.

[10] While average household size is fairly similar across time, I use household size adjusted salaries and expenditures, following Levinson and O'Brien (2019). The results of the paper are not meaningfully different when I use unadjusted salaries and expenditures.

[11] Figure B.7 plots expenditure indexes for the four goods.

In 2021, households spent almost 8 times more on household maintenance compared to 1989. Within the NCI good, expenditures on communication equipment, recreational services, higher education, and other motor vehicle services increased the most. Expenditures within the RMI good have remained fairly stable over time, with the exception of expenditures on sporting equipment and vehicles, vehicle fluids, and medical products.[12] Such heterogeneity in consumption patterns across the NCI, RCI, NMI, and RMI sectors further demonstrates the advantage of the sectoral classification in this paper when compared to the traditional agriculture-manufacturing-services sectoral definitions.

These price and expenditure trends suggest the possibility of changing consumer demand over time, driven by factors beyond traditional income and price effects. To explore the potential implications of evolving consumption patterns for income inequality, I conduct a descriptive counterfactual exercise where I reweigh expenditures on the four goods in all years to keep the good-specific expenditure shares at the level of 1989. This descriptive counterfactual reflects the economy in which the relative demand for goods and services is constant over time. This approach isolates changes in expenditure composition while preserving the observed evolution of factor allocations and technology—both labour share and labour supply evolve according to the data. Counterfactual salaries are derived from the reweighted labour costs conditional on observed labour supply. I use the coefficient of variation (CV)[13] as a measure of income inequality and calculate it for each year using 16 salaries for the four household types employed in four sectors. While this descriptive exercise abstracts from general equilibrium effects, it serves to establish the potential empirical role of changing demand on income inequality—a relationship I examine more rigorously through a structural model in the subsequent sections.

Figure 2 shows a substantial increase in income inequality between 1989 and 2021, consistent with the well-documented rise in income inequality in the US over this period. In 2021, the CV is 21% larger than in 1989. However, the counterfactual scenario with constant expenditure shares shows a steeper increase in inequality, with the CV rising by 59% relative to its 1989 level. This difference in CV trends suggests that changes in consumer demand may have played a role in moderating the rise in income inequality over this period.

[12] Figures B.3-B.6 show expenditures for the NIPA lines over time by type.

[13] Coefficient of Variation (CV): $CV = \frac{SD_{Income}}{Average\ Income}$. I use labour quantities as weights when calculating the CV.

3 Model with Demand Growth Factors (DGFs)

To explore the role of changing demand for goods and services on income inequality, I develop a general equilibrium structural transformation model where changes in the consumption structure arise through a novel channel – demand shifters, given by Demand Growth Factors (DGFs), in addition to relative prices and incomes. The model builds on the canonical structural transformation models, closely following Buera et al. (2022), Comin et al. (2021), Herrendorf et al. (2013), and Buera and Kaboski (2012) in defining the household's problem, and Leon-Ledesma and Moro (2020); León-Ledesma and Satchi (2019), and Herrendorf et al. (2015) in defining the sector's problem. Household's preferences are based on the non-homothetic CES utility specification,[14] which I extend by introducing DGFs. In the model, DGFs arise through good-specific demand growth rates, which reflect how the perceived utility from a good changes over time. Each sector's production technology is based on a CRESH production function with factor-augmenting technical progress.

DGFs capture an evolving component of consumer demand that goes beyond traditional income and price effects. For example, DGFs can account for changes in product quality that are not directly observable in data but are instrumental in the context of technological change (Syverson, 2017). As technologies advance, consumers may derive greater satisfaction from products due to improvements in design, functionality, or durability, even if their prices remain constant. DGFs can also capture shifting consumer tastes. For example, taste shocks are a central component in Baqaee and Burstein (2023). They show that taste shocks can alter how consumers allocate spending across goods, influencing welfare in ways that simple price or income adjustments do not capture.

Beyond quality and taste, DGFs could also capture technological externalities that

[14] Another commonly used specification of preferences is Price-Independent Generalized Linear (PIGL) preferences, used by Arvai and Mann (2022) and Boppart (2014). There are several notable distinctions between PIGL preferences and the non-homothetic CES preferences, as discussed in Comin et al. (2021). First, Comin et al. (2021) note that PIGL preferences rely on specific parametric relationships between income and price elasticities over time, whereas non-homothetic CES preferences do not impose any such parametric restrictions. Second, PIGL preferences are typically limited to two sectors with distinct income elasticities, whereas the non-homothetic CES framework can easily accommodate multiple sectors. The model in this paper examines consumption choices over four good types, which are produced by four sectors. The advantage of PIGL preferences is their ability to allow income elasticities to vary non-linearly with income, which can capture income effects even at very high income levels. However, since this paper uses aggregated data, the need to precisely model income elasticities at extreme income levels is less relevant, and non-homothetic CES preferences are sufficient for capturing the overall demand patterns. Specifically, I estimate the model using aggregated expenditure data at the level of four distinct household types. As shown in Section 5, almost all of the estimated non-homotheticities range between 45-70% in the household-level model. This suggests that the non-homothetic CES preferences effectively capture the income effects across the bulk of the income distribution, minimizing the need for the more complex non-linear variation in elasticities that PIGL preferences offer.

enhance the utility derived from certain goods. For instance, Katz and Shapiro (1985) highlight the importance of network effects, where a product becomes more valuable as more people use it, as is the case with smartphones or social media platforms. DGFs can also represent how the utility of a good increases based on its integration into our daily lives and how extensively it is used. For example, Goolsbee and Klenow (2006) show that the utility derived from internet-based products increases with usage. Using price indices as measures of consumer welfare often underestimates the true value consumers derive from such goods.

3.1 Model Universe

The model includes four aggregate households, denoted by i – non-routine cognitive (nc), routine cognitive (rc), non-routine manual (nm), and routine manual (rm) households. Each household consumes four goods, denoted by j – non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), non-routine manual intensive (NMI), and routine manual intensive (RMI). Preferences differ across household types.

Each good is produced by a single sector that is of the same type as the good it produces and is also denoted by j. Each household supplies labour, denoted by type i, to all four sectors and collects wages from all four sectors. Thus, there are 16 wages that determine income distribution in the model. Each sector employs capital and all four types of labour in production. Production technologies differ across sectors. Household and sector type definitions are as outlined in Section 2.

Similar to Buera et al. (2022), Comin et al. (2021), and Herrendorf et al. (2013), I focus on intratemporal equilibrium allocations and prices. This allows me to abstract from the dynamic aspects of general equilibrium models and instead operate within a static framework. In the model, changes in the demand for goods and services affect factor demand and drive changes in factor prices in equilibrium.

3.2 Households

Preferences of a household i are given by a non-homothetic CES specification with DGFs, shown in equation 1:

$$\max_{\substack{c_{NCI\,t}, c_{RCI\,t},\\ c_{NMI\,t}, c_{RMI\,t}}} u_{i_t}(c_{NCI\,t}, c_{RCI\,t}, c_{NMI\,t}, c_{RMI\,t}) = \Bigg(\sum_{\substack{j=NCI,\,RCI,\\ NMI,\,RMI}} \omega_j^{\frac{1}{\eta}} \big(e^{\lambda_{ij}t}(c_{ijt} + \overline{c}_{ij})\big)^{\frac{\eta-1}{\eta}} \Bigg)^{\frac{\eta}{\eta-1}}, \tag{1}$$

$$s.t. \sum_{\substack{j=NCI,\,RCI,\\ NMI,\,RMI}} p_{jt} c_{ijt} = C_{jt}, \tag{2}$$

were, ω_j is a good-specific non-negative utility weight, η is the elasticity parameter, common across households and goods, c_{ijt} denotes quantity of good j consumed by household i at time t, and $\overline{c}_{ij}$ are household-good specific non-homotheticity parameters or subsistence levels. When non-homotheticity terms are non-zero, the elasticity of substitution will depend on η and non-homotheticity terms.[15] As long as non-homotheticity terms differ across goods and households, the elasticity of substitution will vary across good pairs and households. For this reason, constraining η to be the same across households is not restrictive,[16] and the model has high flexibility in capturing consumption patterns across and within households.

The non-homotheticity terms capture how consumption patterns evolve with income, reflecting that as households become wealthier, the proportion of income allocated to different goods changes. The importance of income effects arising from non-homothetic preferences has been widely noted in the structural transformation literature (Buera et al., 2022; Comin et al., 2021; Boppart, 2014; Herrendorf et al., 2013; Buera and Kaboski, 2012; Matsuyama, 2002).

While non-homothetic CES preferences provide a framework for capturing changes in consumption with income and relative prices, both these channels are ultimately driven by production-side factors, since income and relative prices are determined by production technologies. Therefore, in these models, changes in consumption patterns are still fundamentally supply-driven rather than demand-driven. To address this limitation, I introduce an additional source of changes in demand that is independent of income and

[15] The elasticity of substitution between two goods j and m for household i in a non-homothetic CES framework is

$$\varepsilon_{ijm} = \eta \frac{d\,log\big(\frac{c_{ijt}+\overline{c}_{ij}}{c_{imt}+\overline{c}_{im}}\big)}{d\,log\big(\frac{c_{ijt}}{c_{imt}}\big)}.$$

[16] A special case of this preferences specification is when all non-homotheticity terms are equal to 0. In this case, the preferences are represented by a homothetic CES specification, and η is the elasticity of substitution between consumption goods. In this case, this specification might be too restrictive – assuming that the elasticity of substitution between the four goods is the same is a strong, possibly implausible, assumption. However, as shown in Section 5, all non-homotheticity terms are large, statistically significant, and differ from one another.

price effects and is captured through DGFs. In equation 1, DGFs are expressed by $e^{\lambda_{ij}t}$, where λ_{ij} denotes household-good specific demand growth rates. DGFs capture changes in the consumption structure that arise from shifts in the relative utility households derive from goods over time.

Households maximize their utility subject to a budget constraint, given by equation 2. Following Herrendorf et al. (2013), I restrict the household's expenditure on the four goods in the budget constraint to equal the household's total expenditure in a given period, denoted by C_{jt}, which serves as a proxy for the household's income. In counterfactual analysis, I express the household's total expenditure as a constant share of income. Section 4.3 discusses this step in more detail.

Since the analysis in this paper focuses on intratemporal allocations and prices within a static framework, the model abstracts from intertemporal decision making, such as savings. Solving the household's optimization problem gives rise to a demand system comprising 16 equations – one for each good and household. Equation 3 shows the consumption solution for good c_{ijt}:

$$c_{ijt} = \frac{\omega_j p_{jt}^{-\eta} e^{\lambda_{ij}t(\eta-1)}}{\sum_{\substack{m=NCI,\,RCI,\\ NMI,\,RMI}} \omega_m p_{mt}^{1-\eta} e^{\lambda_{im}t(\eta-1)}} \Bigg(C_{it} + \sum_{\substack{m=NCI,\,RCI,\\ NMI,\,RMI}} p_{mt}\bar{c}_{im} \Bigg) - \bar{c}_{ij}. \tag{3}$$

DGFs appear in both the numerator and the denominator of equation 4, effectively scaling the utility weight from the standard non-homothetic CES framework across periods. Optimal consumption allocations depend not only on prices and income, but also on the demand growth rates. Consumption will shift towards goods with larger demand growth rates. Equation 4 shows consumption of good j relative to good m, accounting for subsistence levels:

$$\frac{c_{ijt} - \bar{c}_{ij}}{c_{imt} - \bar{c}_{im}} = \frac{\omega_j}{\omega_m} \Big(\frac{p_{jt}}{p_{mt}}\Big)^{-\eta} e^{(\lambda_{ij}-\lambda_{im})(\eta-1)t}. \tag{4}$$

The extent to which households substitute towards a good with a higher demand growth rate depends on the difference in demand growth rates between the two goods. For example, if demand growth rates are larger for non-routine-intensive goods, this will tend to increase the relative demand for these goods and, subsequently, factors employed in the production of these goods. Similar to price effects, DGF effects depend on subsistence levels and the elasticity parameter, η, which plays a critical role in enabling and amplifying substitution effects arising from DGFs. When η is lower, households are less responsive to differences in demand growth rates, and the shifts in consumption will be more muted. Conversely, a larger η implies a greater willingness to substitute between goods in response to changing DGFs. As η increases, the model predicts stronger consumption shifts toward goods with higher demand growth rates, magnifying the influence of DGFs on consumption patterns. The increase in consumption of goods with higher demand growth rates, however, is not monotonic, since at sufficiently high values of η, the negative substitution effects from relative price changes can constrain the reallocation of consumption across goods, driven by DGFs.

In this model, changes in demand structure arise with time due to DGFs even if relative prices and household incomes remain constant. Differences in demand growth rates across goods lead to shifts in their respective demand curves. Goods with larger DGFs experience a rightward shift in their demand curves, while goods with relatively lower DGFs see leftward shifts in their demand curves. If production technologies and increases in the supply of factors fail to keep pace with the demand growth for goods with larger DGFs, the rightward shifts in their demand curves will lead to higher consumption of these goods at higher prices.

3.3 Sectors

All sectors minimize their costs from five production factors: the four types of labour – nc, rc, nm, and rm – and sector-specific capital. The cost minimization problem[17] for sector j is given by

$$\min_{\substack{L_{nc\,t}, L_{rc\,t},\\ L_{nm\,t}, L_{rm\,t}, K_t}} r_{jt} K_{jt} + \sum_{\substack{i=nc,\, rc,\\ nm,\, rm}} w_{ijt} L_{ijt} \;\; s.t. \;\; F_j(K_{jt}, \mathbf{L_{jt}}) \geqslant Y_{jt}, \tag{5}$$

$$\mathbf{L_{jt}} \equiv L_{ncj\,t}, L_{rcj\,t}, L_{nmj\,t}, L_{rmj\,t},$$

where r_{jt} is the rental rate of capital, K_{jt}, in sector j at time t; w_{ijt} is the wage for labour provided by household i to sector j, L_{ijt}; and $F_j(K_{jt}, \mathbf{L_{jt}})$ is the production function for sector j subject to output Y_{jt}.

The sector's production problem is based on the CES production function with factor-augmenting technical progress by Herrendorf et al. (2015) and León-Ledesma et al. (2010) and is in a value-added form. Recent empirical findings highlight the importance of substitutability between capital and different labour types based on skills and routine nature of work, linking these differences to changes in wages as technologies become more embedded in production (Acemoglu and Restrepo, 2022; Goos et al., 2014; Autor et al.,

[17]As Herrendorf et al. (2015) note, expressing the firm's problem through cost minimization results in a determinate scale of production, whereas maximization of profits with constant returns to scale leads to indeterminate production scale.

2003). For this reason, I extend this framework by incorporating the Homothetic Constant Ratios of Elasticity of Substitution (CRESH) production function, pioneered by Hanoch (1971). The CRESH specification generalizes the CES production function by allowing the elasticity of substitution to vary between different inputs while maintaining homotheticity, thus more accurately capturing the factor-pair specific differences in substitutability.[18] This specification is particularly relevant in the production structure in this model, in which sectors employ capital and four different labour types that differ based on how routine their work is. The production function is given by equation 6:

$$F_j(K_{jt}, \mathbf{L_{jt}}) = \left[\alpha_{Kj}(e^{\gamma_{Kj}t}K_{jt})^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} + \sum_{\substack{i=nc,\,rc,\\ nm,\,rm}} \alpha_{Lij}(e^{\gamma_{Lij}t}L_{ijt})^{\frac{\sigma_{Lij}-1}{\sigma_{Lij}}}\right]^{\frac{\sigma_j}{\sigma_j-1}}. \tag{6}$$

Here, the α terms represent factor weights, which capture the relative importance of factors in production, and γ_K and γ_L are capital and labour augmenting technical growth rates. CRESH elasticity parameters are denoted by the σ terms. The elasticity of substitution between factor pairs is given by the Allen-Uzawa elasticity (AES), introduced by Allen (1938) and extended by Uzawa (1962).[19] Following Matsuyama (2023), I express the AES between labour of type i and capital in sector j is as

$$\rho_{Lij\,Kj} = \frac{\sigma_{Kjt}\sigma_{Lij}}{\theta_{Kj}\sigma_{Kj} + \sum_{\substack{i=nc,\,rc,\\ nm,\,rm}} \theta_{Lijt}\sigma_{Lij}}, \tag{7}$$

where θ denotes the factor share of the corresponding production factor.

Factor prices are determined in equilibrium. Equation 8 shows the wage expression for each type of labour in each sector, which is equal to the marginal product of labour in that sector. Equation 9 shows the expression for rent in sector j.

$$w_{ijt} = \alpha_{Lij} p_{jt} e^{\gamma_{Lij}\frac{\sigma_{Lij}-1}{\sigma_{Lij}}} L_{ijt}^{-\frac{1}{\sigma_{Lij}}} Y_{jt}^{\frac{1}{\sigma_j}}, \tag{8}$$

$$r_{jt} = \alpha_{Kj} p_{jt} e^{\gamma_{Kj}\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} K_{jt}^{-\frac{1}{\sigma_{Kj}}} Y_{jt}^{\frac{1}{\sigma_j}}. \tag{9}$$

The wage ratio between labour type i in sector j and labour type n in sector m

[18] For additional discussion on CRESH production function, see an excellent overview on non-CES aggregators by Matsuyama (2023).

[19] Another elasticity of substitution that was developed for production functions with more than two inputs is the Morishima elasticity of substitution (MES) (Morishima, 1967). MES captures asymmetric effects in substitution, whereas AES assumes symmetric substitution across inputs, and the symmetry property of AES aligns well with the properties of homothetic functions. For more discussion on the two elasticities of substitution, see Blackorby and Russell (1989) and Blackorby and Russell (1981).

is driven by relative factor weights, prices, technical growth rates, labour supply, and sectoral output, as shown in equation 10. The effects of technical growth rates, factor supply, and output on wages are mediated by CRESH elasticities,

$$\frac{w_{ijt}}{w_{nmt}} = \frac{\alpha_{Lij}}{\alpha_{Lnm}} \frac{p_{jt}}{p_{mt}} \frac{e^{\gamma_{Lij} \frac{\sigma_{Lij}-1}{\sigma_{Lij}}}}{e^{\gamma_{Lnm} \frac{\sigma_{Lnm}-1}{\sigma_{Lnm}}}} \frac{L_{ijt}^{-\frac{1}{\sigma_{Lij}}}}{L_{nmt}^{-\frac{1}{\sigma_{Lnm}}}} \frac{Y_{jt}^{\frac{1}{\sigma_j}}}{Y_{mt}^{\frac{1}{\sigma_m}}}. \tag{10}$$

This production structure captures how sector and factor specific differences in technical growth rates drive structural transformation from the production side. Positive factor augmenting technical growth rates imply a rightward shift in the supply curve for a sector. If the demand curve for the good produced by this sector shifts by a larger extent, households will consume a larger quantity of the good at a higher price in a new equilibrium. This will affect wages of labour employed in the production of the final good, as well as relative wages across sectors, as shown in equations 8 and 10. This interaction between evolving demand and technical progress shows how structural change affects income inequality through two channels: changing consumer demand can increase wages in sectors producing goods with larger DGFs, while technological progress directly affects the relative productivity and wages of different types of labour.

3.4 Equilibrium

A competitive equilibrium is characterized as a set of good and factor prices, consumption and factor allocations, such that households and firms optimize their respective objective functions, and all markets clear.

Households maximize utility by choosing consumption bundles subject to their budget constraints, taking prices and wages as given. The inclusion of DGFs introduces shifts in demand for each good. Households allocate their income across goods in response to prices, income, and DGF-driven demand shifts.

Firms minimize costs by choosing quantities of labour and capital to meet their production requirements given good and factor prices. Each sector employs four labour types and capital, and produces output based on sectoral production technology with factor-augmenting technical growth rates. Factor prices are equal to their marginal products.

In equilibrium, all markets clear – total supply equals total demand in the goods, labour, and capital markets. Equilibrium prices, wages, and capital rents balance supply and demand in the goods and factor markets. In the model, an equilibrium in each period reflects how changes in demand and production technologies shape the allocation of resources and the distribution of income in the economy.

4 Estimation Approach and Identification

In the model, the parameters that govern a household's consumption decision-making include utility weights, ω's, annual demand growth rates, λ's, non-homotheticity terms, $\overline{c}$'s, and the elasticity parameter, η. The parameters that guide a sector's optimal factor allocations are annual factor augmenting technical growth rates, γ's, and CRESH elasticity parameters, σ's. I estimate these parameters separately from the household's and sector's problems using aggregated quarterly expenditure data, discussed in Section 2. I then use these estimates to solve for prices, wages, consumption allocations, and output in a general equilibrium to perform counterfactual analyses.

4.1 Demand System Estimation

The solution to a household's problem gives rise to a demand system of 16 equations – one for each of the four goods consumed by each of the four households, described by equation 3. To account for the dependency between household consumption choices for different goods, as well as the dependency between consumption choices of different households, I consider all consumption equations for all households jointly. Multiplying equation 3 by prices and dividing it by the total expenditure of a household provides an expression for the consumption shares of goods. Adding an error term that captures measurement error, ε_{ijt}, uncorrelated with the exogenous variables, gives the final estimation equation for expenditure share:

$$\frac{p_{jt}c_{ijt}}{C_{it}} = \frac{\omega_j p_{jt}^{1-\eta} e^{\lambda_{ij}t(\eta-1)}}{\sum_{\substack{m=NCI,\, RCI,\\ NMI,\, RMI}} \omega_m p_{mt}^{1-\eta} e^{\lambda_{im}t(\eta-1)}} \left(1 + \sum_{\substack{m=NCI,\, RCI,\\ NMI,\, RMI}} \frac{p_{mt}\overline{c}_{im}}{C_{it}}\right) - \frac{p_{jt}\overline{c}_{ij}}{C_{it}} + \varepsilon_{ijt}. \quad (11)$$

Expressing the demand system using good shares simplifies the system of equations to 12 in place of the original 16. This is because now the dependent variables are expenditure shares, which sum to one for each household. Including all 16 good share equations will result in a singular covariance matrix. To avoid this issue, I drop the estimation equation for RMI goods for each household.[20]

In the model, utility weights on the four goods cannot be negative and have to sum to 1, and η is also constrained to be non-negative. To account for these model restrictions, I follow Herrendorf et al. (2013) and rewrite η and utility weights as follows:

[20]The estimation results do not depend on what equation is dropped.

$$
\begin{aligned}
&\eta = e^{b_1}, \\
&\omega_{nc} = \frac{1}{1+e^{b_2}+e^{b_3}+e^{b_4}}, \quad \omega_{rc} = \frac{e^{b_2}}{1+e^{b_2}+e^{b_3}+e^{b_4}}, \\
&\omega_{nm} = \frac{e^{b_3}}{1+e^{b_2}+e^{b_3}+e^{b_4}}, \quad \omega_{rm} = \frac{e^{b_4}}{1+e^{b_2}+e^{b_3}+e^{b_4}}.
\end{aligned} \tag{12}
$$

Substituting the unconstrained parameters, given by equations 12, into equation 11, with the addition of the error term that represents time-independent preference shifts or measurement error, gives the final system of equations. Following Herrendorf et al. (2013), I also estimate this demand system using non-linear iterated FGLS.[21]

The identification of parameters of interest relies on distinct sources of variation in the data. The elasticity parameter, η, is identified from changes in expenditure shares due to changes in prices for all goods over time. The good-specific non-homotheticity parameters, $\overline{c}$'s, are identified through variation in total expenditures (as a measure of income), while controlling for the price of the good. The utility weight parameters, ω's, are identified from average expenditure shares for each good, reflecting the relative importance of the good in household consumption decisions while accounting for prices and total expenditure. Finally, the demand growth rates, λ's, which give rise to DGFs, are identified from good-specific trends in consumption shares that cannot be explained from changes in total expenditure or prices. The key identifying assumption to obtain estimates of λ's is the presence of systematic time trends in consumption patterns after accounting for price and income effects. Non-linearity of equations is another attribute that aids identification, as discussed in more detail in León-Ledesma et al. (2010).

Before estimating the demand system for the four households, I first estimate the equivalent demand system at the level of the aggregate economy. The aggregate economy demand system contains three consumption share equations – non-routine cognitive, routine cognitive, and non-routine cognitive good equations. I do this to compare how well the non-homothetic CES preferences specification with DGFs, proposed in this model, fits the data compared to the standard non-homothetic CES specification widely used in the structural transformation literature. I also estimate the aggregate model for a longer period using expenditures from the NIPA lines over the period 1960-2023, covering 64 years – a period similar in duration to Herrendorf et al. (2013).

The purpose of using NIPA expenditures in estimation is two-fold. First, using data

[21] Using non-linear IFGLS is a standard way of estimating demand systems. Under the assumption of the error terms not being correlated with the exogenous variables, estimates from the non-linear IFGLS estimator converge to maximum likelihood estimates. For more discussion, see Herrendorf et al. (2013).

over a longer period of time abstracts from short-term fluctuations that might be affecting the estimates. Second, it serves as an expenditure validity check – CEX expenditures have been noted to be underreported compared to expenditures in NIPAs (Aguiar and Bils, 2015). Similar differences in demand growth rates across goods, which drive changes in consumption structure in the model, across both CEX and NIPA expenditures will reinforce the validity of results.

As an additional check, I perform Monte Carlo simulations to verify that this estimation procedure consistently recovers the structural parameters of the demand system in the model. Monte Carlo simulations confirm that the differences in demand growth rates – which drive structural change in the model – are consistently and precisely identified, exhibiting well-behaved sampling distributions centred near the empirical point estimates. The results from Monte Carlo simulations are reported in Appendix C.

Estimation of the demand system at the household level comes with additional challenges. First, estimating the model at the aggregate level reduces the dimensionality of the problem. Second, aggregate economy level data behaves more smoothly compared to data aggregated at the level of household types, since aggregating expenditures smooths out idiosyncratic household-level variation. Both of these considerations are important when dealing with larger non-linear systems of equations. In the model, η and ω's are common across households. To reduce computational complexity, I use estimates of η and ω's from the aggregate demand system, and estimate the remaining household-level parameters, $\bar{c}$'s and λ's, from the household-level demand system. Constraining η and ω's to be the same across households greatly reduces the computational burden while maintaining flexibility in modelling household-level consumption behaviour. When η is the same across households, estimates of household-specific non-homotheticity terms, $\bar{c}$'s, will adjust to capture the household and good-pair specific elasticities of substitution. When ω's are the same across households, estimates of λ's, which can be interpreted as the dynamic component of utility weights, will adjust to capture differences in utility weights across households. As equation 4 shows, it is the differences in the good-specific λ's at the household level that drive changes in consumption structure, rather than their absolute values. Thus, changes in consumption structure that arise through DGFs are well identified.

4.2 Sector's Problem Estimation

The solution to a sector's problem with the production function, given by equation 6, consists of five first-order conditions (FOCs) – one for each factor hired by the sector. FOCs for labour type i and capital, hired by sector j, are given by equations 8 and 9.

Production functions and the corresponding FOCs for four sectors give rise to a system of 24 equations that determine production structure and sectors' choices in equilibrium. Similarly to the household's problem, I consider these equations jointly. Estimating all four sectors together allows for the error terms to be correlated across sectors. I normalize these equations prior to estimation.

León-Ledesma et al. (2010) highlight the importance of normalization in production problems and emphasize the need to jointly estimate the FOCs along with the production function. Normalization resolves the issue of output and production factors being measured in different units. Estimating FOCs alongside the production function ensures that cross-equation parameter constraints are met, facilitating joint identification of the technical growth rates. Further, without including the non-linear production function as part of the estimated system, normalization points in the linear FOCs may be absorbed by constants, leading to biased estimates.

Following Herrendorf et al. (2015), I normalize the production function using geometric averages for output, four types of labour, and capital, denoted by $\overline{Y}_j$, $\overline{L}_{ij}$, and $\overline{K}_j$, and the arithmetic average of time, denoted by $\bar{t}$.[22] I then take FOCs with respect to labour and capital using the normalized production function. Applying the logarithmic transformation to the production function and FOCs and adding an error term, which captures measurement error or productivity shocks, to each equation gives the sector's final estimation equations:

$$\log(Y_{jt}) = \log(\overline{Y}_j) + \frac{\sigma_j}{\sigma_j - 1}\log\Bigg[\frac{\sigma_j - 1}{\sigma_j}\frac{\sigma_{Kj}}{\sigma_{Kj}-1}\,\overline{\theta}_{Kj}\left(e^{\gamma_{jk}(t-\bar{t})}\frac{K_{jt}}{\overline{K}_j}\right)^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} \tag{13}$$

$$+ \sum_{\substack{i=nc,\,rc,\\ nm,\,rm}} \frac{\sigma_j - 1}{\sigma_j}\frac{\sigma_{Lij}}{\sigma_{Lij}-1}\,\overline{\theta}_{Lij}\left(e^{\gamma_{Lij}(t-\bar{t})}\frac{L_{ijt}}{\overline{L}_{ij}}\right)^{\frac{\sigma_{Lij}-1}{\sigma_{Lij}}}\Bigg] + \epsilon_{yjt},$$

$$\log(w_{ijt}) = \log(p_{jt}) + \log\left(\frac{\overline{\theta_{Kj}Y}_j}{\overline{L}_{ij}}\right) + \gamma_{Lij}\frac{\sigma_{Lij}-1}{\sigma_{Lij}}(t-\bar{t}) + \frac{1}{\sigma_{Lij}}\log\left(\frac{L_{ijt}}{\overline{L}_{ij}}\right) + \frac{1}{\sigma_j}\log\left(\frac{Y_{jt}}{\overline{Y}_j}\right) + \epsilon_{wjt}, \tag{14}$$

$$\log(r_{jt}) = \log(p_{jt}) + \log\left(\frac{\overline{\theta}_{Lij}\overline{Y}_j}{\overline{K}_j}\right) + \gamma_{Kj}\frac{\sigma_{Kj}-1}{\sigma_{Kj}}(t-\bar{t}) + \frac{1}{\sigma_{Kj}}\log\left(\frac{K_{jt}}{\overline{K}_j}\right) + \frac{1}{\sigma_j}\log\left(\frac{Y_{jt}}{\overline{Y}_j}\right) + \epsilon_{rjt}. \tag{15}$$

[22] León-Ledesma et al. (2010) normalize their production function by multiplying and dividing each variable by its arithmetic average. In contrast, Herrendorf et al. (2015) use geometric averages for all variables except time. As they point out, the arithmetic average provides an approximation that is accurate near the approximation point but becomes less reliable further away from it. On the other hand, using geometric averages ensures that the normalized production function holds everywhere. For this reason, I follow Herrendorf et al. (2015) in using geometric averages for normalization.

Equations 13-15 describe the final equations for each sector. As a result of such normalization, relative weights on capital and labour equal geometric averages of the income shares of these factors, $\overline{\theta}$, scaled by CRESH elasticities.[23] Adding an error term, representing productivity shifters or measurement error, to all equations for each of the four sectors gives the final system of 24 equations. I estimate this system jointly using non-linear 3SLS. Following Herrendorf et al. (2015), I use lagged variables for endogenous right-hand side variables as instruments.[24]

Identification of factor augmenting technical growth rates and CRESH elasticities relies on intertemporal variation in sectoral output, prices, factor inputs, and factor prices. I take geometric averages of factor income shares, θ's, from the data. Sector-specific elasticity parameters, σ_j's, and labour-and capital-sector specific elasticity parameters, σ_{Lij}'s and σ_{Kj}'s, are identified from the variation in factor prices due to changes in aggregate output and factor inputs. Technical growth rates, γ_{Lij}'s and γ_{Kj}'s, are identified from trends in factor prices after accounting for changes in aggregate output and factor inputs. The presence of time-dependent changes in wages and capital rents that are not explained by changes in output and factor inputs is a key identifying assumption for factor augmenting technical growth rates. The joint estimation of the production function and FOCs enforces cross-equation restrictions and, through the production function's non-linearity, imposes additional restrictions on the estimates, helping to separate the effects of technological change from those of factor substitution.

4.3 Counterfactual Analysis Approach

When performing counterfactual analysis, I solve for 16 consumption allocations, c_{ijt}, 4 sectoral outputs, Y_{jt}, 4 good prices, p_{jt}, and 16 wages, w_{ijt}, in a system of 44 equations that define general equilibrium of the model. These equations include 16 consumption choice equations from the household's problem, given by equation 3; 4 sectoral production

[23]In the case of CES production function, exponents equal income shares with normalization, similar to Cobb-Douglas production functions, as in Herrendorf et al. (2015), whereas in normalized CRESH production functions income shares are also scaled by elasticity parameters. The normalized income shares for labour and capital are given by

$$\overline{\theta}_{Lij} \equiv \overline{\left[\frac{w_{ij}L_{ij}}{p_{ij}Y_j}\right]} = \alpha_{Lij}\frac{\sigma_j}{\sigma_j - 1}\frac{\sigma_{Lij}-1}{\sigma_{Lij}}\left[\exp(\gamma_{Li}\overline{t})\overline{L}_{ij}\right]^{\frac{\sigma_{Lij}-1}{\sigma_{Lij}}}\overline{Y}_j^{\frac{1-\sigma_j}{\sigma_j}},$$

$$\overline{\theta}_{Kj} \equiv \overline{\left[\frac{r_jK_j}{p_jY_j}\right]} = \alpha_{Kj}\frac{\sigma_j}{\sigma_j - 1}\frac{\sigma_{Kj}-1}{\sigma_{Kj}}\left[\exp(\gamma_{Kj}\overline{t})\overline{K}_j\right]^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}}\overline{Y}_j^{\frac{1-\sigma_j}{\sigma_j}}.$$

[24]For more discussion on the use of lagged variables as instruments when estimating a production problem, see Herrendorf et al. (2015).

functions, given by equation 13; 20 FOCs for labour and capital, given by equations 14-15; and 4 market clearing equations, where output produced by industry j is equal to the sum of goods type j consumed by each household, as shown in equation 16:

$$Y_{jt} = c_{nc\,jt} + c_{rc\,jt} + c_{nm\,jt} + c_{rm\,jt}. \tag{16}$$

This system is overidentified, as the number of equations exceeds the number of unknowns (44 equations and 40 unknowns). Including the 4 goods market-clearing equations imposes additional constraints on consumption and output solutions. These constraints ensure the system behaves well by limiting extreme or unstable allocations, facilitating a smoother convergence in equilibrium. I use estimates from the household's and sector's problems, estimated as discussed in Sections 4.1 and 4.2, when solving for counterfactual equilibriums. I use the same data for counterfactual analysis that I use for estimating the household and sector problems, which is the aggregated household-level expenditure data.

In equilibrium, changes in consumption arise due to DGFs and changes in income and relative prices. DGFs are a function of time and annual demand growth rates, estimated from the household's problem. Household income depends on wages that are established in equilibrium. Relative prices are also an equilibrium object. Equation 3 describes a household's consumption choices subject to total expenditure as a proxy for income. In counterfactuals, I set a household's total expenditure to be a constant share of income, which is 93.5% – the average income share in the data. This is consistent with Carroll and Summers (1991); Campbell and Mankiw (1989), who show that consumption and income growth rates are highly correlated.

I use household-level labour income from the CEX data, since consumption expenditures are recorded at the household level.[25] However, in the CPS data, which I use to allocate labour shares to occupations for each sector, labour income is measured at the individual level. To reconcile this difference, I reweigh the aggregate number of households, which is the sum of BLS weights from the CEX, such that the number of households is expressed in terms of individual incomes from the CPS, rather than household incomes from the CEX. For example, if the average individual income of a particular labour type in the CPS is \$50,000, and a corresponding household type in the CEX earns \$60,000, I equate the household income in the CEX to the individual income in the CPS and adjust the household weight by a factor of 1.2 to account for this difference. Since I sum expenditures at the aggregate household level, this reweighing does not affect the expenditure data and is solely used to align incomes in the CPS and CEX data for counterfactual analysis. Matching incomes across the consumption and production data ensures that

[25] Using individual income from the CEX instead of household income produces very similar results.

income effects are accurately captured in equilibrium.

This approach relies on the assumption that income earners within the household are of the same type, which is supported by the literature. Dupuy and Galichon (2014) show that individuals tend to match with partners who have similar occupations, while Greenwood et al. (2014) document increasing assortative mating by education and occupation over time in the U.S. Additionally, Eika et al. (2019) show that assortative mating accounts for a significant portion of cross-sectional inequality in household income.

Changes in production arise due to technical progress and factor supply. Technical progress is driven by annual factor augmenting technical growth rates, estimated from the sector's problem. The model does not allow solving for 16 wages and 16 labour allocations simultaneously without imposing additional structural assumptions. Thus, when performing counterfactual analysis, I treat factor allocations as given and take factor supply at the sector level from the data. This approach implies that labour distribution across sectors does not change in response to demand shifts, which could be possible due to strong labour market frictions. Indeed, recent literature shows the presence of strong labour market frictions. Autor et al. (2021) show that the labour market effects of the China trade shock persisted for at least a full decade after the shock's peak. Hershbein and Stuart (2020) show that recessions have long-lasting effects on local labour markets, with effects persisting for decades. Artuç et al. (2010) estimate high costs of switching sectors for workers affected by trade liberalization, implying substantial labour market frictions. Furthermore, in the absence of labour market frictions, occupational wages would be the same across sectors, which is not the case (Dustmann and Meghir, 2005).

While the persistence of strong labour market frictions is evident over the short and medium term, it is unlikely that there is no labour reallocation across sectors due to changing demand over longer periods of time. It is possible that the true effects of changes in the demand structure on wages and income inequality are more muted when accounting for changes in the distribution of labour across sectors. This is because the reallocation of labour towards a sector lowers wages in that sector through increasing labour supply, as shown in equation 8. This is also why the presence of labour market frictions is one of the channels that allows changes in demand to affect wages and income inequality. In the presence of strong labour market frictions, and, hence, limited ability by the sector to pool more labour to produce more output, increases in the demand for the good will result in an equilibrium with a higher price for the good. This will increase wages for labour employed by the sector. To explore how changes in demand affect wages through labour market frictions, I conduct additional counterfactual exercises that include reallocation of labour, reported in Section 7.3.

Since the model is set in a static framework and does not impose any structure on intertemporal capital accumulation or investment behaviour, I take capital rent and quantity from the data when performing counterfactual analysis.

The baseline model in the counterfactual analysis solves the general equilibrium using estimates from the household and sector problems. For the remainder of the paper, I refer to effects arising from DGFs as *demand effects*. Note that DGFs affect demand for goods directly through demand growth rates, and indirectly through non-homotheticities due to changes in income and relative prices in equilibrium. I refer to effects due to factor augmenting technical growth rates as *production effects*. In the counterfactual without demand effects, I solve for general equilibrium by setting $t = 1$ in the 16 consumption allocation equations. This keeps the preference structure constant at the level of 1989 throughout the analysis period. In the counterfactual without production effects, I solve for general equilibrium by setting $t = 1$ in the 4 sectoral production functions and 20 FOCs for labour and capital. This keeps technical progress at the level of 1989 for all years in the data. The differences in wages between the baseline model and the two counterfactuals capture demand and production effects on wages.

5 Estimation Results

This Section presents estimation results from the demand system and production problem, described in Sections 3.2 and 3.3. First, I present estimates from the non-homothetic demand system with DGFs at the level of the aggregate economy. I compare these results, as well as the model's ability to fit the data, with those from the standard non-homothetic demand system. I then present estimation results from the demand system with four households, followed by estimation results from the production problem with four sectors. These estimated parameters govern households' and sectors' decision making in general equilibrium.

5.1 Evaluating CES Specifications: Non-homothetic CES with DGFs vs Non-homothetic CES

To assess the performance of the non-homothetic CES preferences with DGFs compared to the standard non-homothetic CES specification, commonly used in the structural transformation literature, I estimate both specifications using data for the aggregate economy using CEX data for 1989-2021 and NIPA data for 1960-2023. The non-homothetic CES specification is based on Herrendorf et al. (2013). The inclusion of DGFs introduces time-dependent changes in consumption structure, which could be driven by technological advances, product quality improvements, or other factors. Table 1 shows the FOCs for each of the specifications and lists estimated parameters. I estimate the demand systems for each CES specification using non-linear iterated FGLS, as discussed in Section 4.1.

Table 2 presents the estimation results for the two CES specifications using both CEX and NIPA data, and Figure 3 illustrates the fit of expenditure shares over time for each of the models for the CEX data. The non-homothetic CES model with DGFs, denoted by the black long dashed line, outperforms the non-homothetic CES without DGFs, given by the blue long dashed line, across all goods. It captures the non-linear shifts in expenditure shares across time more accurately, especially for non-routine intensive goods. The fit of NMI expenditure share is particularly precise.

The Akaike Information Criterion (AIC) in Table 2 corroborates this visual assessment. The AIC value is lower for the model with DGFs, indicating the model's superior performance. Accounting for time dependent changes in demand structure through DGFs, in addition to changes due to income and relative prices, provides the model with greater flexibility and improved accuracy in modelling long-term consumption patterns.

In terms of estimated parameters, the estimate of η is lower in the model with DGFs, although the difference is not statistically significant. This suggests that when accounting for time-varying effects of demand growth rates, consumers are relatively less responsive to changes in prices. The inclusion of DGFs also leads to significant changes in the estimated utility weights. Most notably, the weight for routine manual intensive goods is substantially larger when DGFs are included. It is possible that the non-homothetic CES specification underestimates the importance of routine manual goods in consumer preferences when not accounting for time-varying demand shifts. Non-homotheticity terms differ slightly between the two models.

The estimates in Table 2 show significant heterogeneity in demand growth rates across goods. Notably, NMI goods exhibit the highest annual demand growth rate (0.112), followed closely by RCI goods (0.110). In contrast, RMI goods have the lowest demand growth rate (0.063). Such differences in demand growth rates imply differential growth in demand across sectors. Sectors producing goods with higher demand growth rates experience faster demand growth, potentially leading to higher labour demand and wages in these sectors.

When comparing estimates from the CEX and NIPA, I find remarkable consistency in the pattern of demand growth rates, despite the differences in time periods and data sources. The demand growth rates in the NIPA sample appear to be a rescaled version of those in the CEX sample, maintaining similar relative magnitudes across goods. Both sets of results show the highest demand growth rates for NMI and RCI goods, with RMI goods having the lowest demand growth rates. The differences in demand growth rates drive changes in consumption structure, and they appear to be stable across both datasets and time periods, reinforcing the validity of the results. Furthermore, including demand growth rates improves the precision of estimation over longer time horizons, as evidenced by the lower standard errors, particularly for non-homotheticity estimates, when DGFs are included. Additional results from Monte Carlo simulations, reported in Table C.1 and Figure C.1, show that the estimation procedure consistently recovers the structural parameters of interest in the model with DGFs, particularly the differences in demand growth rates that drive changes in consumption patterns.

Including DGFs in the non-homothetic CES framework offers several important insights into structural change and income inequality. The significant and heterogeneous demand growth rates suggest that demand for goods and services is not static but evolves over time. This dynamic aspect of demand, which is absent in standard models, can help explain persistent shifts in consumption patterns that are not fully accounted for by changes in income or relative prices. Thus, DGFs provide an additional channel through which structural change can affect the distribution of labour income across sectors.

5.2 Household-level Estimates

I now turn to estimating the model for the four aggregate households to capture heterogeneity in consumption patterns across households based on their nature of work.[26] Figure 3 shows the fit of expenditure shares for the four goods in the model estimated at the household level, denoted by the dashed green line. Figure A.2 shows the fit of log quantities for each of the four goods consumed by each of the four households. Both figures demonstrate that the model provides a strong fit to the data and effectively captures the non-linearities in consumption patterns over time.

Table 3 presents the estimates of subsistence levels and annual demand growth rates for each household. To put these estimates into perspective, Table 4 reports subsistence levels relative to the household's average consumption for each good, as well as differences in the demand growth rates. Panel A of Table 4 shows that subsistence levels account for a substantial portion of average consumption across all households and goods. The majority of non-homotheticity terms are more than or close to 50% of average consumption. The magnitude of the non-homotheticity estimates is similar to those in Herrendorf et al. (2013), who estimate a demand system based on the non-homothetic CES for services, manufacturing, and agriculture. These results reaffirm the importance

[26] In the CEX data, household occupations are reported at the occupation group level. I define the type of occupation group based on the occupational composition of the group from the CPS data. Occupation groups are coarse in CEX, and it is possible that each occupation group contains occupations that belong to the other three types. Thus, differences in estimates between different household types, reported in Tables 3 and 4 can be considered as the lower bounds of true estimates.

of non-homotheticities in capturing consumption patterns, consistent with findings in the literature (Buera et al., 2022; Comin et al., 2021; Boppart, 2014; Herrendorf et al., 2013; Buera and Kaboski, 2012; Matsuyama, 2002).

The subsistence levels vary substantially across households and goods. For all households, the RMI good has the largest absolute and relative subsistence levels, suggesting that this category of goods includes many essential goods that households consume regardless of income level, albeit with different intensities across households. For both non-routine and routine cognitive households, the second largest subsistence level is that of the NCI good, while for both manual households – the RCI good. Both cognitive households also have higher absolute and relative subsistence levels across all good categories. This could reflect higher baseline consumption standards for households whose work involves a lot of cognitive tasks, possibly due to factors such as education-related expenses or lifestyle differences. These differences suggest that household composition is important for structural change arising from income effects, complementing work by Buera et al. (2022) on skill-biased structural change.

The annual demand growth rates show significant variation across goods and households. The NMI and RCI goods consistently have the highest demand growth rates across all households, with NMI good having the highest growth rate. This suggests that the perceived value or quality of these goods has been increasing more rapidly over time, potentially due to technological advancements (Syverson, 2017) or changes in tastes due to taste shocks (Baqaee and Burstein, 2023). Conversely, the RMI good consistently has the lowest demand growth rate. This pattern suggests a shift in consumer demand towards the NMI and RCI goods over time, while shifting away from the RMI good. These changes in demand for final goods lead to changes in demand for labour producing these goods.

Panel B in Table 4 shows differences in the demand growth rates for each of the four households. They are all statistically significant, and their differences across households are also statistically significant. The largest difference between the demand growth rates for both non-routine households at 2.4 p.p. is the difference between the NMI and NCI good growth rates. For routine households, the largest difference is between the RCI and NCI good growth rates at 2 p.p. The difference between the RMI and NCI growth rates is negative for all households, varying from -3.3 p.p. for non-routine cognitive households to -1.2 p.p for routine manual households. These differences in demand growth rates across households further reaffirm the importance of household composition in driving shifts in consumption patterns.

5.3 Sector-Level Estimates

Table 5 reports estimates from the production problem for the four sectors. Panel A presents estimates of annual factor-augmenting technical growth rates. Across all sectors, factor augmenting technical growth rates are positive for non-routine cognitive labour, with the highest growth rate in the NMI sector at 1.1%. In contrast, technical growth rates are negative for routine cognitive labour in all sectors, with the largest decline in the RCI sector at -3.3%. This difference aligns with the literature on routine-biased technological change (Acemoglu and Restrepo, 2022; Goos et al., 2014; Autor et al., 2003). Technical growth rates for both non-routine and routine manual labour are also negative across all sectors, but their magnitudes are smaller compared to those of routine cognitive labour. This pattern suggests that while technological change is negatively affecting the wages of manual workers, the impact is not as severe as for routine cognitive workers. Capital augmenting technical growth rates are positive in manual intensive sectors and negative in cognitive intensive sectors.

Factor specific elasticity parameters show considerable variation both within and across sectors, highlighting the importance of using a flexible CRESH specification instead of a more restrictive CES function.[27] Figure 4 shows Allen-Uzawa elasticities of substitution (AES) by sector. AES estimates are reported in Table A.1.

Each sector has a unique pattern of substitutability among inputs. For instance, the NCI sector demonstrates high substitutability between non-routine cognitive and non-routine manual labour (2.568), while the RMI sector shows high substitutability between routine cognitive and routine manual labour (2.391). Routine manual and non-routine manual labour are the most substitutable in the RCI sector, while the AES estimates for the NMI sector are the most similar across factor pairs. The highest degrees of substitutability are often observed between different labour types rather than between capital and labour. For example, in the RCI sector, the AES between non-routine manual and routine manual labour is 2.891, the highest among all elasticities.

The estimation results provide compelling evidence for the importance of DGFs in shaping consumption patterns. The household-level estimates show significant heterogeneity in demand growth rates and subsistence levels across different households and goods. The sector-level estimates show varying patterns of factor-augmenting technical growth rates and elasticities of substitution, aligning with existing literature on skill-biased and routine-biased technological change. The results demonstrate that both shifting con-

[27] I also estimate the more restrictive CES production function. I do this by estimating the system of 24 equations, given by equations 13-15 for each sector, while equating all sector specific σ's, which gives the CES production structure. Table A.2 reports estimates from this problem. The results are similar to those obtained using the CRESH production structure.

sumer demand and technological change play key roles in driving structural change. The heterogeneity observed in both consumption preferences and production technologies sets the stage for the counterfactual analysis, which explores how these estimated parameters guide households' and sector's decision making, affecting wage distribution in equilibrium.

6 Counterfactual Analysis

This Section performs counterfactual analysis to quantify the impact of demand effects that arise through DGFs on wages across households employed in different sectors. I isolate the role of changing demand in shaping income distributions by comparing wages in the baseline model with those in the counterfactual without demand effects, as described in Section 4.3.

6.1 Main Counterfactual Scenario

Figure 5 presents the results of the main counterfactual scenario. It illustrates the wage distribution across 16 household-sector pairs in 2021 for the baseline model, denoted by black dots, and the counterfactual without demand effects, denoted by blue dots. Non-routine cognitive households remain steadily at the top of the income distribution, irrespective of their employment sector. Wages are the lowest in routine intensive sectors, consistent with Acemoglu and Restrepo (2022); Goos et al. (2014), and Autor et al. (2003). The middle of the income distribution includes households employed in non-routine intensive sectors.

The differences in wages between the baseline model and the counterfactual capture demand effects that arise due to DGFs. In the absence of demand effects, the income distribution is notably different. Households employed in the RCI and NMI sectors have lower wages – 10% lower in the RCI sector, and 15% lower in the NMI sector. In contrast, the wages of households employed in the RMI sector are 25% higher. In the counterfactual without demand effects, the bottom of the income distribution includes all but non-routine cognitive households employed in the RCI sector, followed by households employed in the NMI sector. The bottom of the income distribution is lower in the counterfactual without demand effects, while the top of the income distribution is higher, indicating a widening of the income distribution.

These changes in wages come from changes in prices, as shown by equation 8. Figure 6 shows changes in prices over time in the baseline model and counterfactuals with no demand and no production effects. The demand effects, captured by the difference between the black and blue lines, matter the most for the NMI and RMIl sectors, followed by the

RCI sector. Consistent with differences in the demand growth rate estimates in Table 4, DGFs lead to an increase in prices for the NMI and RCI goods, reflecting rising relative demand for these goods, and a decrease in price for the RMI good. Prices for both NMI and RMI goods are driven primarily by demand effects, whereas prices for NCI and RCI goods – primarily by production effects, captured by the difference between the black and blue lines. Production effects do not seem to have a large effect on the prices of the NMI and RMI goods.

Figure 7 shows the evolution of wages over time in the baseline model and the two counterfactuals for each of the 16 household-sector pairs. Similar to Figure 6, production effects matter the most for cognitive intensive sectors. They increase wages for non-routine cognitive households, and lower wages for all other households, consistent with factor augmenting technical growth rate estimates from Table 5. Demand effects slightly offset the negative production effect for households in the RCI sector. In the NMI sector, the negative production effects are offset to a large extent by positive demand effects, especially for manual households. For both non-routine manual and routine manual households, demand effects dominate production effects, resulting in higher wages. DGFs appear to mitigate the negative impacts of automation on these workers. Demand effects for workers in the RMI sector are negative. For manual workers, they are similar in magnitude to production effects, lowering the wages of these workers.

6.2 Importance of Preference Heterogeneity

The results in Tables 3 and 4 show that preferences differ across households. Cognitive households have larger subsistence levels. Differences in the demand growth rates between the RCI and NCI goods are larger for routine households, while differences in the demand growth rates between the NMI and NCI goods are larger for non-routine households. Non-routine cognitive households have some of the largest differences in demand growth rates. Heterogeneity in preferences matters if household composition is changing over time, and over the period of 1989-2021, household composition in the US has undergone dramatic changes: the share of non-routine cognitive households has increased by 24 p.p., the share of routine cognitive households has decreased by 7 p.p., the share of non-routine manual households has decreased by 5 p.p., and the share of routine manual households has decreased by 12 p.p. To examine the importance of changing household composition for demand effects, I perform a counterfactual that keeps household shares constant at the 1989 level throughout the analysis period. This counterfactual adjusts only consumer composition to capture changes in demand effects, leaving labour allocations the same as in the baseline model.

Figure 8 plots wages for the 16 household-sector pairs in 2021 for the baseline and counterfactual with constant household composition. The results show that up to 20% of demand effects arise due to changes in household composition, underscoring the importance of preferences heterogeneity and changes in household composition when exploring structural transformation due to evolving demand. For the RCI sector, demand effects are 8% when household composition is fixed, and 10% with varying household composition. For the RMI sector, these numbers are 13% and 15%, and for the NMI sector – 20% and 24%, respectively. Figures A.21 and A.22 further illustrate these differences by plotting prices and wages for each one of the 16 household-sector pairs over the years.

As the share of non-routine cognitive households, who have some of the largest DGFs, grows over time, the demand effects also become larger. Non-routine cognitive households also tend to have higher wages compared to the other households, as shown in Table B.1. This shows that, rather than inequality begetting more inequality, to an extent, income inequality appears to be self-moderating through demand effects.

7 Channels of DGF Effects and Robustness

In this Section, I perform several robustness checks and explore key channels through which DGFs influence wages and income distributions. Specifically, I focus on the role of elasticities, subsistence levels, and the presence of labour market frictions.

7.1 Elasticities

This Section builds on the observation that the relative consumption of two goods depends on the elasticity parameter, η, as shown in equation 4 in Section 3.2. Greater elasticity implies a greater willingness to substitute between goods in response to changing DGFs, thus amplifying consumption reallocation across goods due to evolving demand. When η is lower, households are less responsive to differences in demand growth rates, and the shifts in consumption will be more muted. As η increases, the model predicts stronger consumption shifts toward goods with higher demand growth rates. However, this is true up to a point, since larger η also drives the negative substitution effect due to changes in relative prices. Based on equation 4, as long as inequality 17 holds, positive effects due to demand growth rates will dominate negative price substitution effects, and relative consumption of the good with the larger demand growth rate will increase,

$$e^{(\lambda_{ij}-\lambda_{im})(\eta-1)t} > \big(\frac{p_{jt}}{p_{mt}}\big)^{-\eta}. \tag{17}$$

Since prices are an equilibrium object, different values of η can change relative prices such that relative price substitution effects can become greater than DGF effects, leading to a decrease in relative consumption of the good with the larger demand growth rate. To explore how counterfactual results differ based on elasticity, I consider three scenarios: Leontief case, $\eta = 0$, scenario with lower elasticity than in the baseline model, $\eta = 1.5$, and scenario with larger elasticity, $\eta = 4.5$. In the baseline model, $\eta = 2.7$.

Figure 9 shows that higher elasticities amplify the effects of DGFs on wages, however, this effect is nonlinear. In the Leontief case, $\eta = 0$, there are minimal differences between wages in the baseline model and in the counterfactual without demand effects. This result is intuitive, as zero elasticity implies that households cannot substitute between goods in response to changing DGFs. The impact of DGFs on the wage distribution is negligible in this case.

As η increases to 1.5, the demand effects start to appear, as shown in Panel B. They are, however, still smaller compared to the main counterfactual when $\eta = 2.7$. When η is 4.5, the effects are also smaller than in the main counterfactual, suggesting that negative relative price substitution effects counteract some of the DGF effects. This is especially prominent from price counterfactuals for the NMI sector, illustrated in Figure A.28.

7.2 Subsistence Levels

Subsistence levels are the other parameters that affect changes in relative consumption due to both relative prices and DGFs. Table 4 shows that subsistence levels account for a substantial portion of households' consumption for all four goods and all four households. This implies that the presence of large non-homotheticities restricts consumption reallocation in response to changes in relative prices or differences in demand growth rates, since at lower income levels, a larger proportion of income is dedicated to meeting subsistence needs, leaving less room for adjustments based on prices or DGFs. When subsistence levels are set to 0, the relative price and DGF effects operate fully across all income levels. This increased responsiveness can lead to larger shifts in relative consumption, resulting in larger wage effects due to DGFs.

Figure 10 shows that, indeed, when non-homotheticity parameters are set to 0, the magnitude of wage differences between the baseline model and the counterfactual without demand effects is larger. For example, in the RCI sector, demand effects increase from 10% in the model with subsistence levels to 15% when setting all subsistence levels to 0. The pattern of effects is the same in both cases with and without subsistence levels.

7.3 Labour Market Frictions

In the main counterfactual analysis, I take sector level labour allocations as given from the data. This approach assumes that the distribution of labour across sectors remains the same regardless of changes in demand. This is possible, for example, due to strong labour market frictions. Reallocation of labour towards sectors that produce higher-demanded goods will lower wages in the sector, as shown in equation 10. Improved ability of labour to shift towards sectors with higher demand growth rates will allow sectors to increase production, leading to more output and lower prices in equilibrium. This suggests that labour market frictions are an important channel for the effects of DGFs on wages.

I explore the implications of the assumption of strong market frictions for results by adjusting labour allocations in counterfactuals. Specifically, I adjust labour quantities based on relative growth in output quantities over time, which serves as a proxy for changes in demand for final goods and, thus, labour producing these goods. This adjustment assumes that labour reallocates to sectors proportionally with the sector's relative output growth. This is a strong assumption, since labour allocations also depend on changes in production technologies, which are not taken into account in this labour market adjustment. Therefore, it presents an extreme scenario, which also serves as a robustness check. To isolate the importance of shifts in labour across sectors, I adjust labour in production only, leaving household distribution as is.

To get the relative output growth rates, I first regress the log of aggregate quantity for each of the four goods produced by the four sectors on a linear time trend, unadjusted for any other controls. The trend estimates, reported in Table 6, capture annual output growth rates for each sector. The output growth rate estimates corroborate earlier findings on the growing demand for the RCI and NMI goods – the RCI and NMI sectors have the largest growth rates at 1.2% and 1.0%, respectively.

Next, I calculate the average output growth rate across the four sectors and compare it with the sector specific growth rates. The differences between the sector specific growth rates and the average growth rate capture relative growth in output for the four sectors and determine sectoral labour adjustment rates. The average output growth rate is 0.775%. The differences between the average growth rate and sectoral growth rates for the four sectors are -0.475 p.p. for the NCI sector, 0.425 p.p. for the RCI sector, 0.225 p.p. for the NMI sector, and -0.175 p.p. for the RMI sector.

I use the adjustment rates to reweigh labour in the counterfactual with no demand effects. That is, in the counterfactual, I scale down labour in sectors that have relatively faster output growth in the baseline model, and scale up labour in sectors that have relatively slower output growth in the baseline model. For example, I reweigh labour employed in the RCI sector in year t by multiplying labour quantity from the data by $(1 - 0.00425 * t)$, where 0.00425 is the adjustment rate and is the difference between the RCI output growth rate and the average output growth rate, reported in Table 6. The adjustment rates sum to 0, so that the size of the labour market is the same as in the data, and only the distribution of labour across sectors changes. Within each sector, these adjustment rates are applied uniformly across all labour types.

In 2021, the adjusted labour quantities in the counterfactual with no demand effects are 16.32% higher in the NCI sector, 13.52% lower in the RCI sector, 6.78% lower in the NMI sector, and 6.40% higher in the RMI sector. The wage differences between the baseline model and the counterfactual with adjusted labour allocations are smaller, but the pattern of results is robust, as shown in Figure 11. Sectors RCI and NCI have relatively larger labour adjustments and show larger differences in wage effects between the main and adjusted counterfactuals. In the counterfactual with adjusted labour, wages are now lower for households employed in the NCI sector, whereas in the main counterfactual without demand effects wage differences were negligible. In contrast, wage differences for households in the RCI sector are now much smaller, since the effects from reallocation of labour in this counterfactual counteract demand effects that arise through DGFs. The output of the NCI sector in this counterfactual is also larger with more labour employed in the sector, whereas the output of the RCI sector is lower, as shown in Figure A.33.

Like the elasticities of substitution, larger labour market frictions facilitate demand effects in this framework, leading to larger wage effects in equilibrium arising from DGFs. Subsistence levels, on the other hand, hinder these effects by limiting households' responsiveness in consumption allocations to DGFs.

8 Implications of DGF-Driven Structural Change

The counterfactual analysis shows that DGFs play an important role in determining wages. This Section explores the broader implications of the DGF-driven changes in demand for income inequality and discusses how the reallocation of economic activity through demand effects is related to changes in GDP growth.

8.1 Income Inequality

In the counterfactual without demand effects, incomes at the bottom of the income distribution are lower, whereas incomes of households at the top of the income distribution are higher, as seen in Figure 5. Such changes in the income distribution suggest a worsening of income inequality in the absence of demand effects. To explore the extent to which income inequality differs between the baseline model and counterfactual with no demand effects, I calculate the coefficient of variation (CV) for each year in the data for the two scenarios. Figure 12 illustrates the evolution of income inequality over time, measured by the CV, for the baseline model and a set of counterfactuals.

The CV in the baseline model, depicted by a black line in Figure 12 Panel A, fits the CV in the data, depicted by a grey dashed line, well over the analysis period. The blue line denotes the CV in the counterfactual without demand effects. In the absence of evolving demand, income inequality is higher throughout the entire period. The difference between the blue and black lines is also increasing, illustrating the growing importance of demand effects over time. Table 7 Panel A provides a quantitative summary of these changes. In the absence of demand effects driven by DGFs, income inequality would have increased substantially more between 1989 and 2021. The change in the CV in the counterfactual scenario without demand effects is 73% larger than in the baseline model.

Panel B in Figure 12 illustrates the magnitudes of demand and production effects relative to the scenario when both of these effects are absent. The green line shows what income inequality would be in a scenario where preference structure and production technologies are at the level of 1989 throughout the analysis period. In this case, income inequality remains fairly stable over time, slightly decreasing towards the end of the analysis period. Counterfactuals with demand and production effects illustrate very different income inequality trajectories. In the counterfactual with production effects, income inequality is substantially larger compared to the scenario with no demand or production effects, reaching a 40% difference in 2021. These results are in line with the findings in the literature that show significant negative effects of technological change on income inequality (Acemoglu and Restrepo, 2022; Autor et al., 2003). However, Panel B shows that demand effects are also sizeable and offset a large share of production effects. Throughout the years, demand effects are smaller by, on average, 8 p.p. However, they are slowly catching up in magnitude to production effects, and in 2021, they were at 38% – just 2 p.p. smaller than production effects.[28]

Table 7 Panel B summarizes changes in CV in the three counterfactuals from Figure 12 Panel B. In the benchmark scenario with no production or demand effects, the change in CV between 1989 and 2021 is -0.017, showing a slight decrease in income inequality over time. In contrast, in the scenario that allows for changes in production technologies, income inequality increases by 0.069, which is 0.086 more than in the benchmark counterfactual. In the scenario with demand effects driven by DGFs, income inequality

[28]Since these results are based on different counterfactuals, their purpose is to show the relative magnitudes of demand and production effects compared to the scenario with neither demand nor production effects. The effects are not additive because they are based on solutions to different general equilibrium problems.

decreases by 0.098 between 1989 and 2021 – 0.081 more compared to the benchmark. The magnitude of changes in income inequality due to demand effects is over 94% of that of production effects. This shows that evolving consumption demand has played a crucial role in moderating the rise of income inequality over the past three decades, which has been exacerbated by changes in production technologies.

These results complement and extend the existing literature on technological change and income inequality. While studies like Acemoglu and Restrepo (2022) and Autor et al. (2003) have emphasized the role of skill-biased and routine-biased technological change in driving income disparities, the analysis in this paper highlights the substantial counterbalancing effect of changing consumption patterns. The demand-side effects, captured by DGFs, substantially offset increases in income inequality due to technological change. These results also complement Baqaee and Burstein (2023), who emphasize the importance of changes in consumer demand on the allocation of spending across goods and welfare outcomes.

8.2 Baumol's Cost Disease and Productivity Slowdown?

The results from the counterfactual analysis in this paper provide a new perspective on Baumol's cost disease (Baumol, 1967) and its implications for productivity growth and income inequality in advanced economies. Figure 13 shows that economic activity, driven by changing demand structure via DGFs, is shifting towards less productive sectors – namely, the NCI, RCI, and NMI sectors.[29] This shift aligns with Baumol's prediction that the economy would shift towards labour-intensive sectors[30] where productivity improvements are more challenging to achieve. This productivity slowdown has garnered significant attention in the literature (Duernecker et al., 2017; Fernald, 2015).

The results in this paper suggest that the demand driven slowdown in productivity growth is not necessarily problematic. From the demand perspective, there appears to be a tradeoff between growth and equity. As evident from Section 8.1, income inequality is lower in the presence of evolving demand, and DGFs appear to be of crucial importance in offsetting the widening of the income inequality due to changes in production technologies. The demand-driven reallocation of economic activity towards less productive,

[29]Sector-level factor augmenting technical growth rates, estimated from production functions of the form

$$F_j(K_{jt}, \mathbf{L_{jt}}) = e^{\gamma_j t}\Big[\alpha_{Kj}(K_{jt})^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} + \sum_{\substack{i=nc,\,rc,\\ nm,\,rm}} \alpha_{Lij}(L_{ijt})^{\frac{\sigma_{Lij}-1}{\sigma_{Lij}}}\Big]^{\frac{\sigma_j}{\sigma_j-1}} \tag{18}$$

using elasticity parameter from Table 5, are -0.01443(0.00058) for the NCI sector, -0.00836 (0.00024) for the RCI sector, -0.00060 (0.00036) for the NMI sector, and 0.00003 (0.00052) for the RMI sector.

[30]Figure B.8 plots labour shares by sector over time.

more labour-intensive sectors improves the wages of workers employed in these sectors, whose wages would have otherwise decreased dramatically due to the negative effects of technological change.

This paper contributes to the growing literature that calls for a reconsideration of how we interpret and measure economic progress in developed economies, illustrating the complex relationship between changing consumption patterns, productivity growth, and structural change. The results in this paper align with the argument put forward by Vollrath (2020), who states that slower GDP growth in developed economies is largely a consequence of positive economic and demographic trends, rather than a sign of failure. The findings in this paper support this view. The move towards less productive sectors in a developed economy, such as the US, may be welfare-enhancing, echoing Baqaee and Burstein (2023), who highlight the importance of considering demand-side factors when assessing economic welfare.

The results in this paper also resonate with the recent literature questioning the negative connotations associated with slowing productivity growth in advanced economies. For instance, Aghion et al. (2023) argue that official productivity statistics may underestimate true productivity growth by failing to fully capture quality improvements and new product varieties. In the model in this paper, DGFs could reflect such unmeasured quality improvements in addition to increased consumer valuation of these goods. The computing power of a laptop has increased dramatically over the past 30 years. What appears in the data as decreased productivity might be a reflection of increased production complexity, requiring more time and resources, due to higher product quality. Syverson (2017) also discusses the challenges in measuring productivity in service-oriented economies, suggesting that official statistics may underestimate true productivity growth by failing to fully capture quality improvements and new varieties of services. Thus, it is possible that some of the DGF effects come from changes in the quality of final goods. What share of the DGF effects can be attributed to quality improvements remains a fruitful avenue for future research.

9 Conclusion

This paper examines the importance of evolving consumer demand for income inequality in the US over 1989-2021. While much of the existing literature has focused on how technological progress affects wages, I demonstrate that changing consumption patterns play a significant and previously underappreciated role in shaping income disparities.

I develop a general equilibrium structural transformation model that incorporates time-varying demand shifters – Demand Growth Factors (DGFs). The proposed model allows for a more comprehensive analysis of the forces driving structural change and income inequality. Estimates of DGFs show significant heterogeneity in consumer demand across goods and households, indicating that the demand for final goods and services has evolved considerably over the analysis period in ways not fully captured by income or price effects alone.

Counterfactual analysis shows that demand effects, driven by DGFs, play a crucial role in moderating income inequality. In the absence of these effects, the increase in income inequality between 1989 and 2021 would have been 73% larger. Changing demand has particularly benefited workers in the NMI and RCI sectors, partially offsetting negative production effects for households employed in these sectors. The magnitude of these demand effects is substantial – the effects of evolving demand on income inequality nearly match those of technological change, but in the opposite direction.

The paper also highlights the importance of preference heterogeneity across households. Up to 20% of the DGF-driven demand effects on wages arise from shifts in household composition over time, particularly the increase in non-routine cognitive households. The consumption patterns of these typically higher-income households contribute to moderating overall income inequality, and an increase in the share of these households helps to temper income inequality through demand effects.

The findings in this paper have important implications for our understanding of structural change, productivity growth, and income inequality in developed economies. The results suggest that the demand-driven shift towards labour-intensive sectors with lower productivity growth, consistent with Baumol's cost disease, may not necessarily be detrimental when viewed through the lens of income inequality.

The results in this paper pave the way for several avenues of future work. First, further analysis of the mechanisms behind DGFs, including the role of product quality improvements and technological externalities, could provide important insights into the nature of evolving consumer demand. Second, developing a dynamic version of the model would help us better understand how demand shifts affect wages when we account for households' saving decisions and the accumulation of capital over time. Finally, cross-country comparative analysis could shed light on whether the moderating effect of demand on inequality is a universal phenomenon or specific to certain economic contexts.

This paper demonstrates the critical importance of considering both supply-side and demand-side factors in analyzing long-term trends in income distribution. By highlighting the role of changing consumption patterns in shaping income inequality, it provides a more comprehensive framework for understanding the interplay between technological progress and consumer demand in advanced economies.

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Figures and Tables

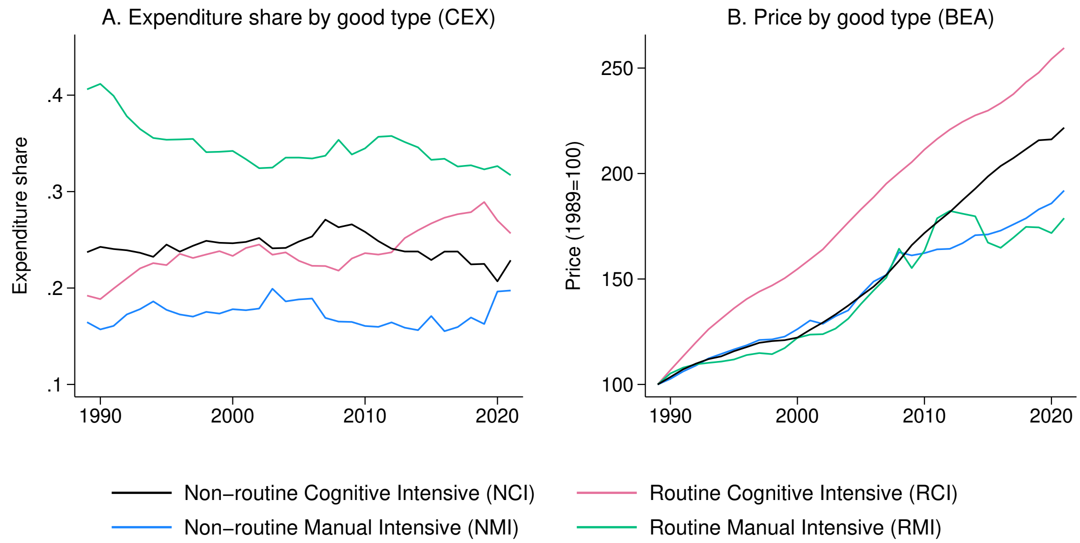

Figure 1: Expenditure Shares and Prices by Good Type

Note: Panel A plots expenditure shares by good type using Consumer Expenditure Survey (CEX) data for 1989-2021. Good types are based on the labour composition of their main producing industry, as discussed in Section 2. Expenditure shares are calculated from aggregated expenditures for each of the four goods for the sample of households with reference persons aged 25-65 with non-missing occupations, excluding the top and bottom 1% of households by total salary in each year. The aggregation is performed using BLS sampling weights adjusted for months in scope. Panel B plots price indexes (1989=100) by good type using BEA Personal Consumption Expenditure price data. Good type price indexes are calculated as a weighed average of NIPA price indexes that comprise the good type, weighted by NIPA expenditures.

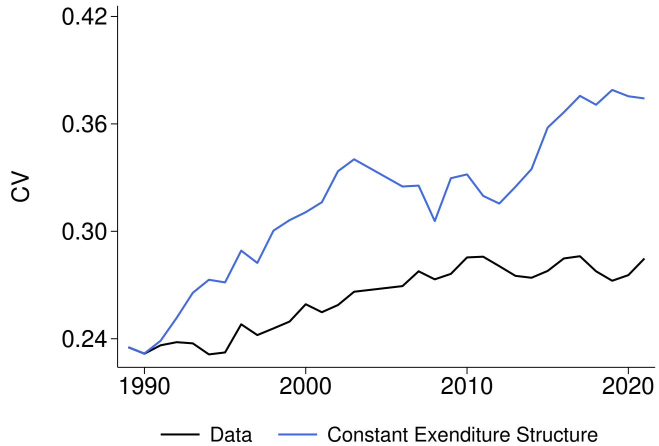

Figure 2: Coefficient of Variation Over Time

Note: Coefficient of variation: CV = SD Income/Average Income. CV is calculated across 16 household-sector pairs using labour quantities as weights. Household and sector definitions are as discussed in Section 2. Constant expenditure structure CV is obtained in a descriptive counterfactual exercise that keeps expenditure shares on the four goods fixed at the level of 1989 over time, while allowing factor supply and labour share to change over time. Salaries are calculated from the counterfactual labour costs given labour supply. Sample and data construction follow Figure 1. Years 2004-2005 are excluded due to changes in salary reporting in the CEX. See Appendix B for details.

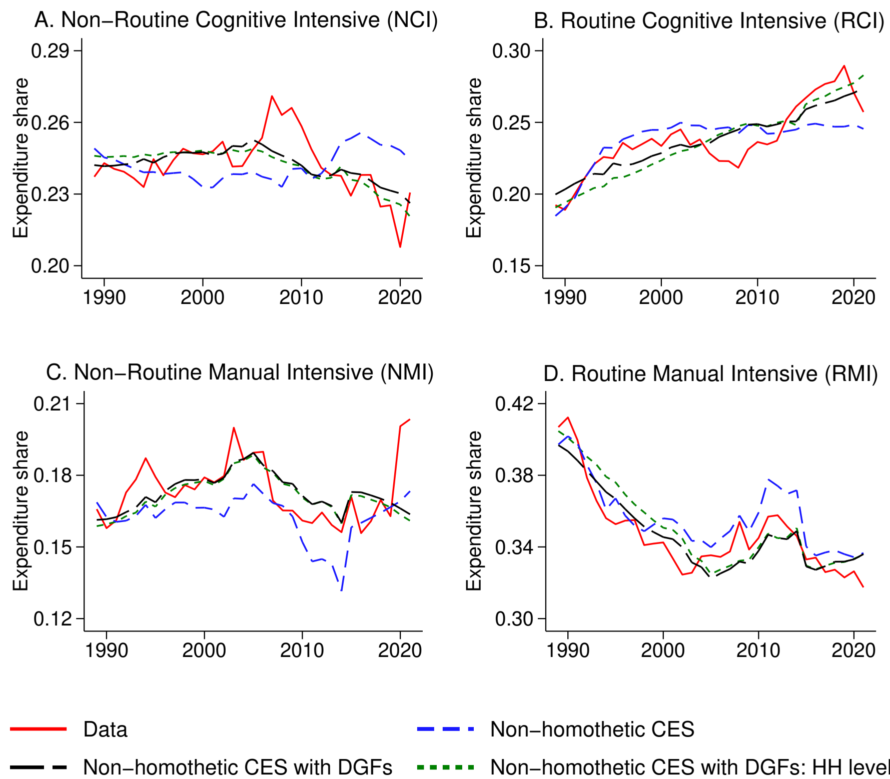

Figure 3: Fit of Aggregate Expenditure Shares by Good

Note: "Non-homothetic CES" and "Non-homothetic CES with DGFs" lines show fitted shares from the aggregate economy estimation, while "Non-homothetic CES with DGFs: HH level" shows fitted shares from the household-level estimation. Estimates are obtained using aggregated data as in Figure 1. Household and good definitions are as discussed in Section 2. For the aggregate economy, the estimated demand system consists of FOCs for 3 expenditure shares – non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), and non-routine manual intensive (NMI) good shares. Equation for expenditure share of routine manual intensive (RMI) good was dropped to avoid a singular error covariance matrix. Household-level demand system consists of 12 equations – 3 expenditure share equations for each of the four aggregate households. The estimated FOCs for each utility function specification are in Table 1. Each demand system is estimated jointly using iterated non-linear FGLS. Estimates used to get fitted shares are reported in Tables 2 and 3.

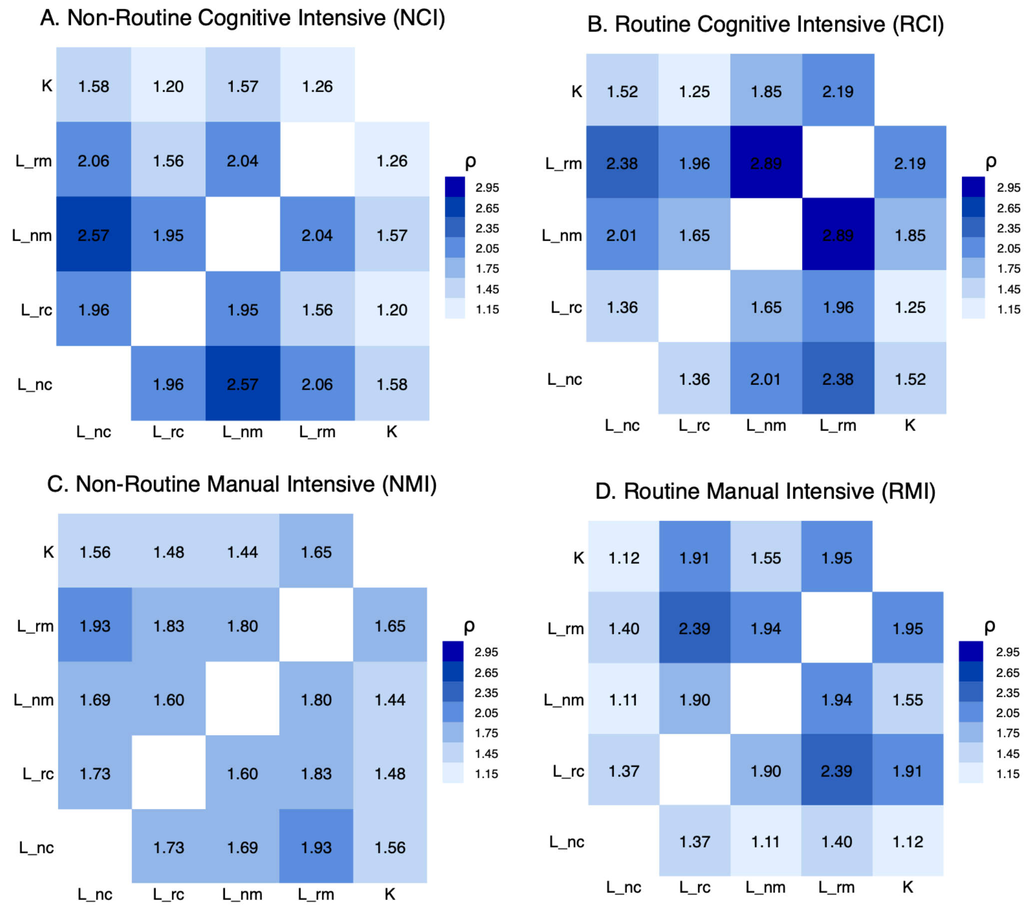

Figure 4: Allen-Uzawa Factor-Pair Elasticities of Substitution by Sector

Note: Allen-Uzawa elasticities (AES) are calculated based on equation 7 using CRESH elasticity estimates from Table 4 and geometric averages of factor shares. Table A.1 reports all AES and their standard errors. L_{nc} is non-routine cognitive labour, L_{rc} – routine cognitive labour, L_{nm} –non-routine manual labour, L_{rm} – routine manual labour, and K – capital. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors – NCI, RCI, NMI, and RMI, as discussed in Section 2.

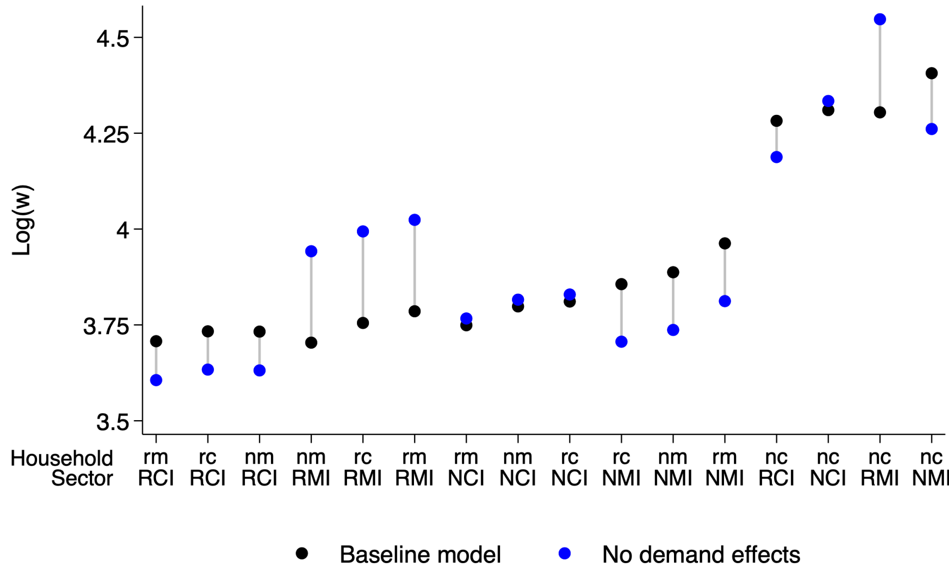

Figure 5: Wages In the Baseline Model and Counterfactual Without Demand Effects in 2021

Note: Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. “Baseline model” shows wages predicted by the model based on estimates from Tables 2, 3, and 4. “No demand effects” shows wages in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3. Figure A.20 illustrates wages in the baseline model and counterfactual with no demand effects pre-Covid for the year 2019.

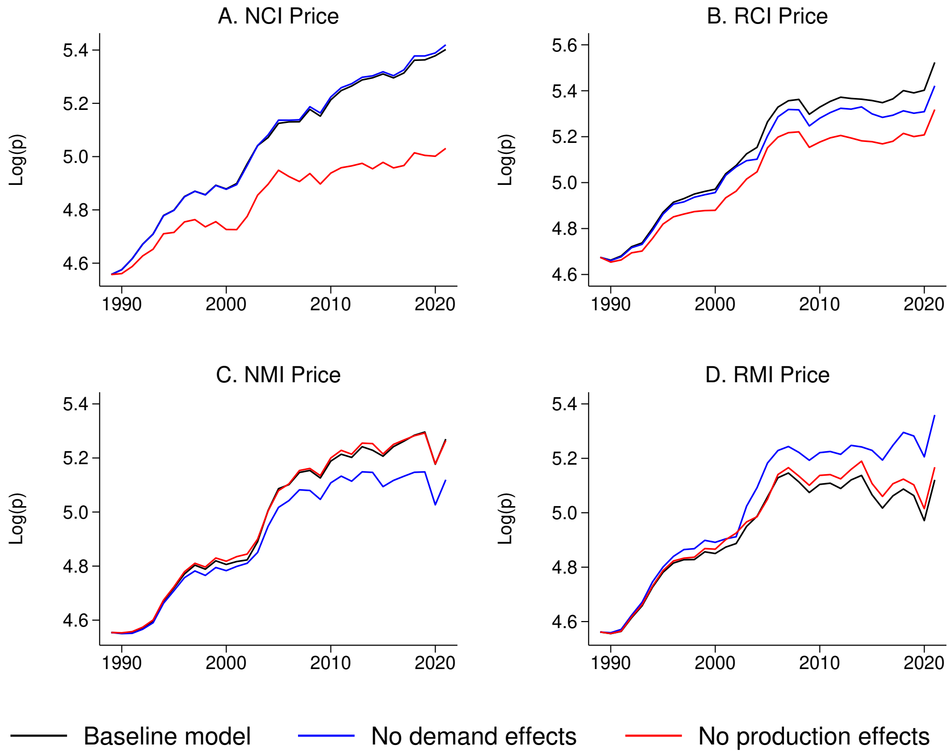

Figure 6: Prices In the Baseline Model and Counterfactual Without Demand Effects Over Time

Note: Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. "Baseline model" shows prices predicted by the model based on estimates from Tables 2, 3, and 4. "No demand effects" shows prices in the counterfactual when setting DGFs to be at the level of 1989 for all years. "No production effects" shows prices in the counterfactual when setting technical progress at the level of 1989 for all years, as discussed in Section 4.3.

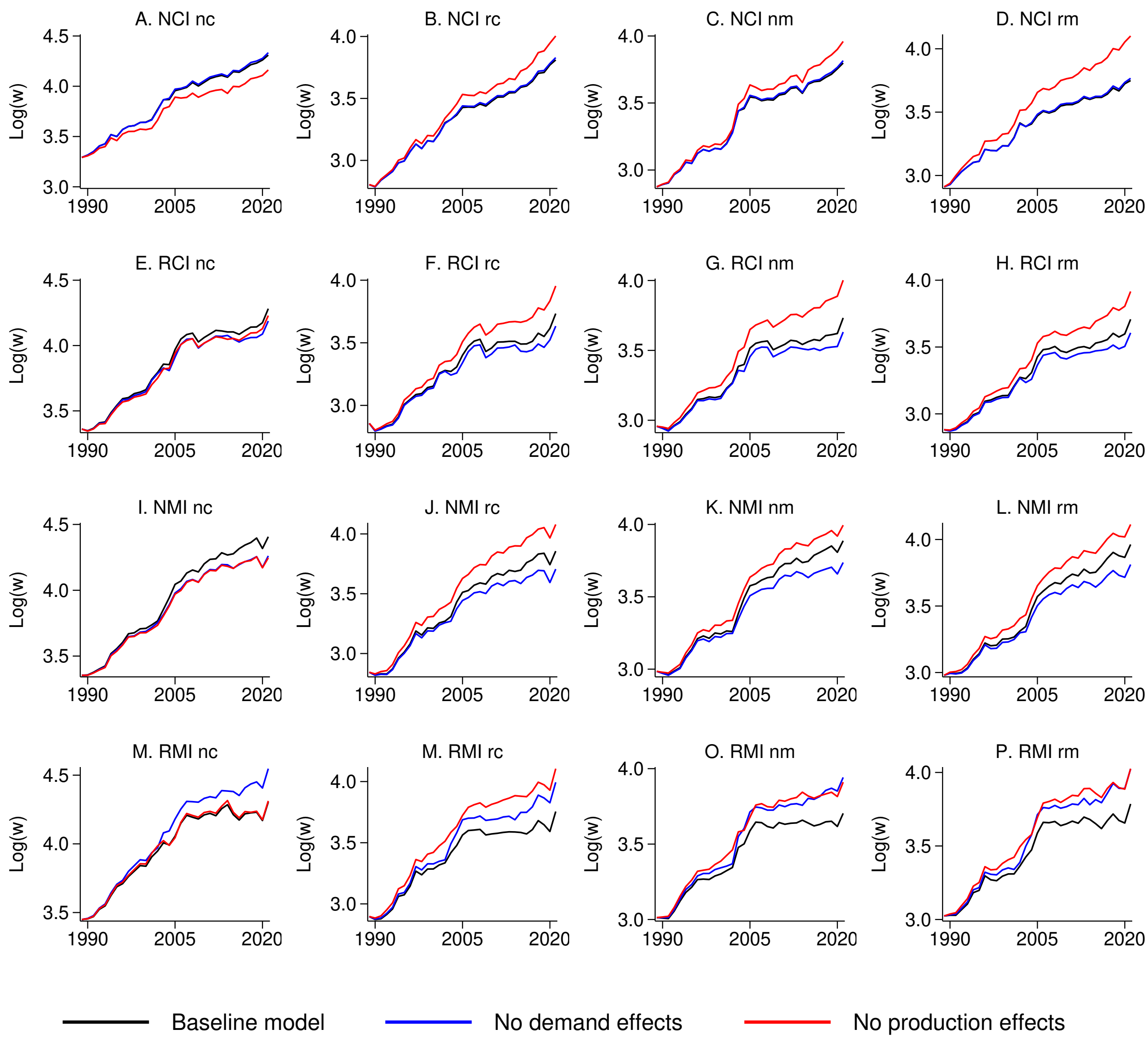

Figure 7: Wages In the Baseline Model and Counterfactual Without Demand Effects Over Time

Note: Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. "Baseline model" shows wages predicted by the model based on estimates from Tables 2, 3, and 4. "No demand effects" shows wages in the counterfactual when setting DGFs to be at the level of 1989 for all years. "No production effects" shows wages in the counterfactual when setting technical progress at the level of 1989 for all years, as discussed in Section 4.3.

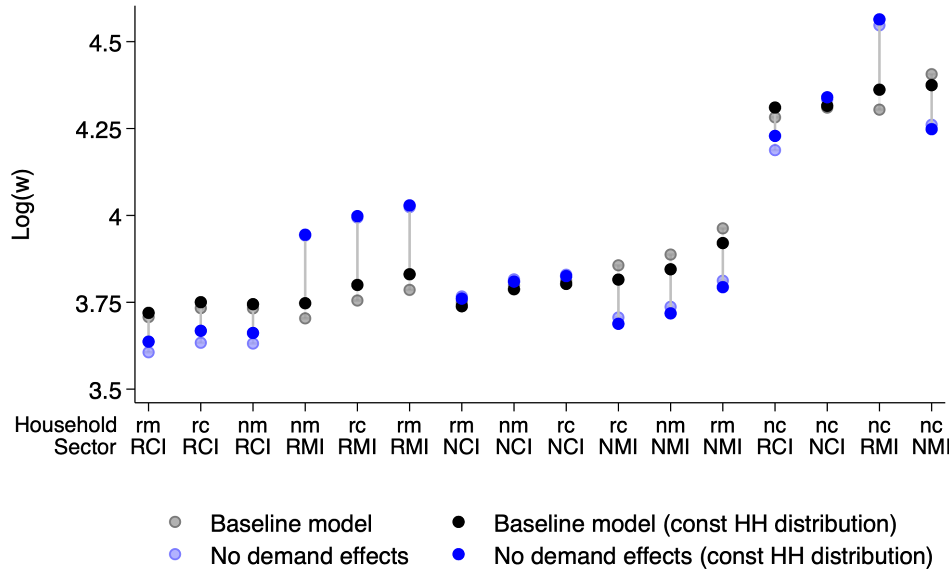

Figure 8: Wage Differences in 2021 with Constant Household Distribution

Note: Baseline model and counterfactual with constant household distribution solve for equilibrium allocations and prices when keeping keeping household shares at the level of 1989 for all years. Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. "Baseline model" shows wages predicted by the model based on estimates from Tables 2, 3, and 4. "No demand effects" shows wages in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3. Wage differences over time are illustrated in Figure A.21.

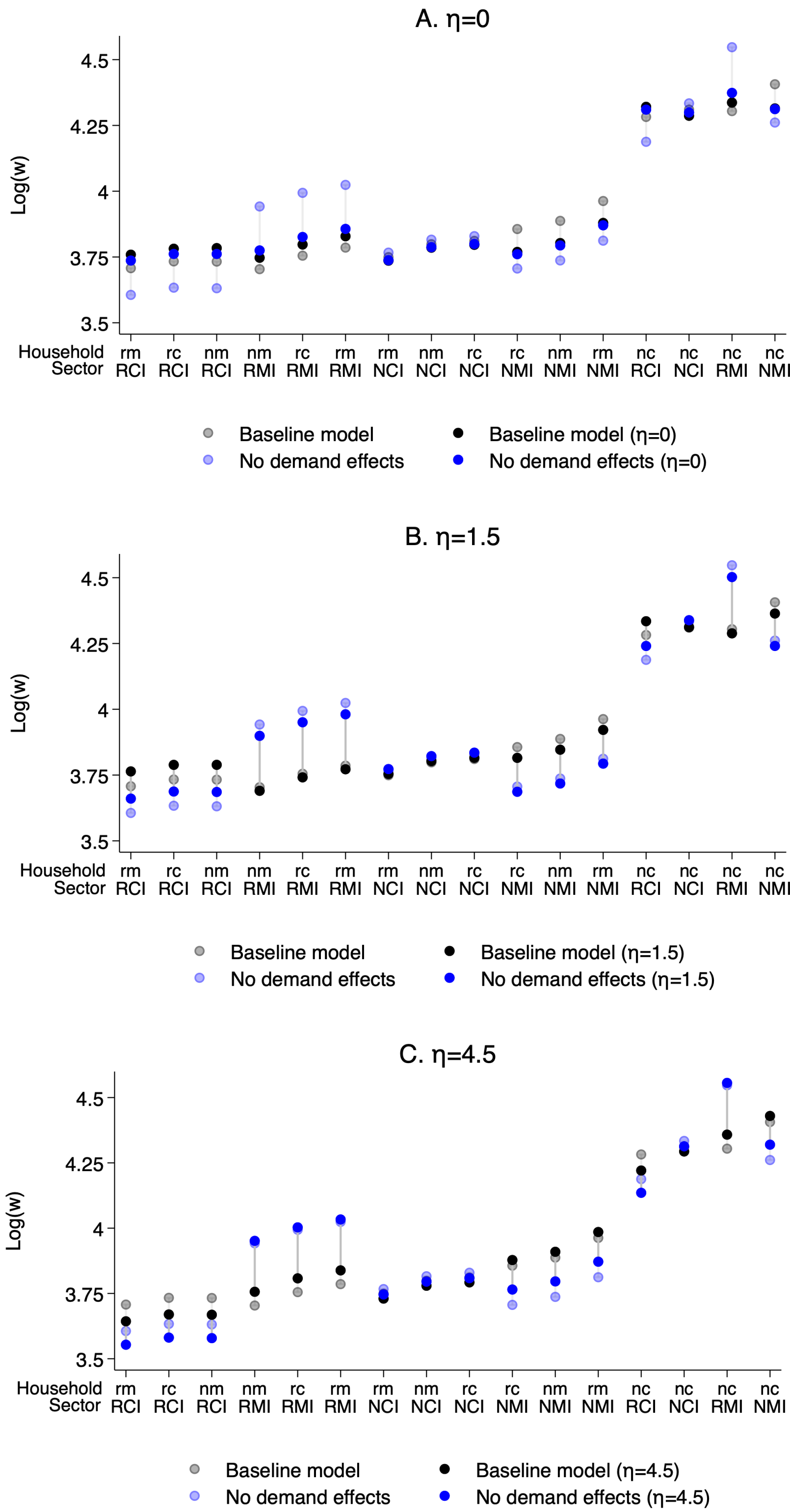

Figure 9: Wage Differences in 2021 For Varying Elasticity

Note: Wages are shown for 16 household-sector pairs when solving for equilibrium using different values of the elasticity parameter in household problem, η. Nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. Wage differences over time are illustrated in Figures A.23-A.27.

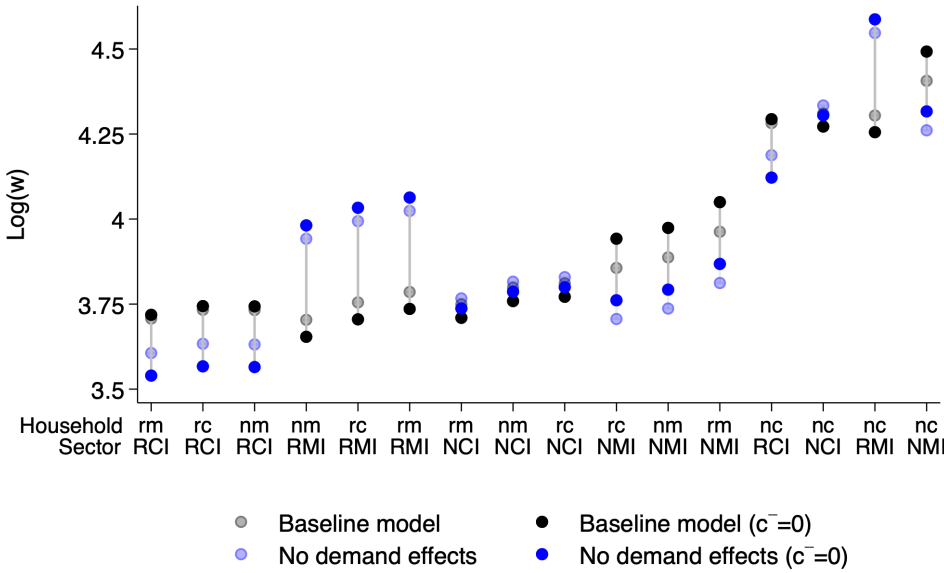

Figure 10: Wage Differences in 2021 with no Subsistence levels

Note: Baseline model and counterfactual with no subsistence levels solve for equilibrium allocations and prices when setting non-homothetic terms to 0. Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. "Baseline model" shows wages predicted by the model based on estimates from Tables 2, 3, and 4. "No demand effects" shows wages in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3. Wage differences over time are illustrated in Figure A.29.

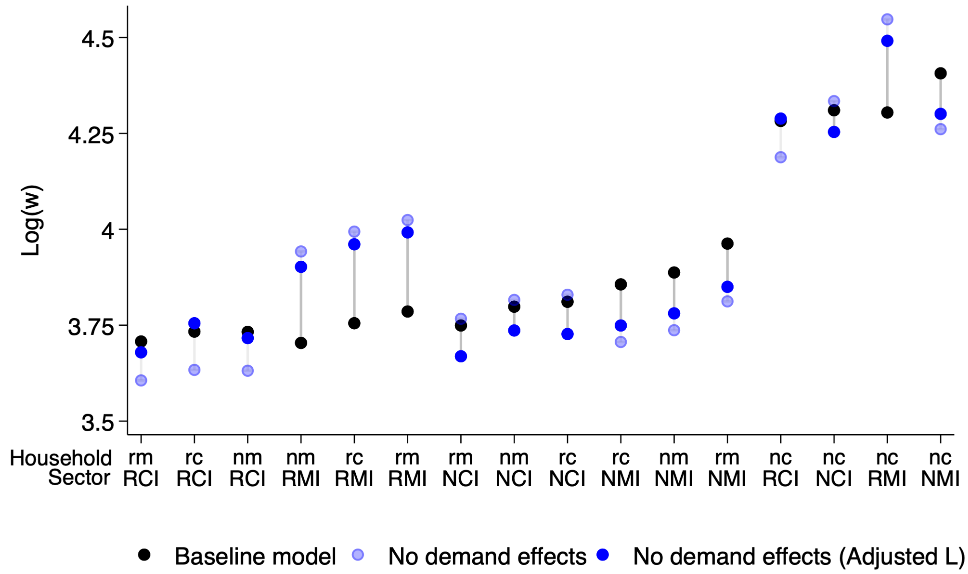

Figure 11: Wage Differences in 2021 For Adjusted Labour Allocations

Note: Labour allocations are adjusted at the sector level based on sector specific relative output growth rates, as discussed in Section 7.3. Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Household and sector definitions are as discussed in Section 2. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors, as discussed in Section 2. "Baseline model" shows wages predicted by the model based on estimates from Tables 2, 3, and 4. "No demand effects" shows wages in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3. Wage differences over time are illustrated in Figure A.31.

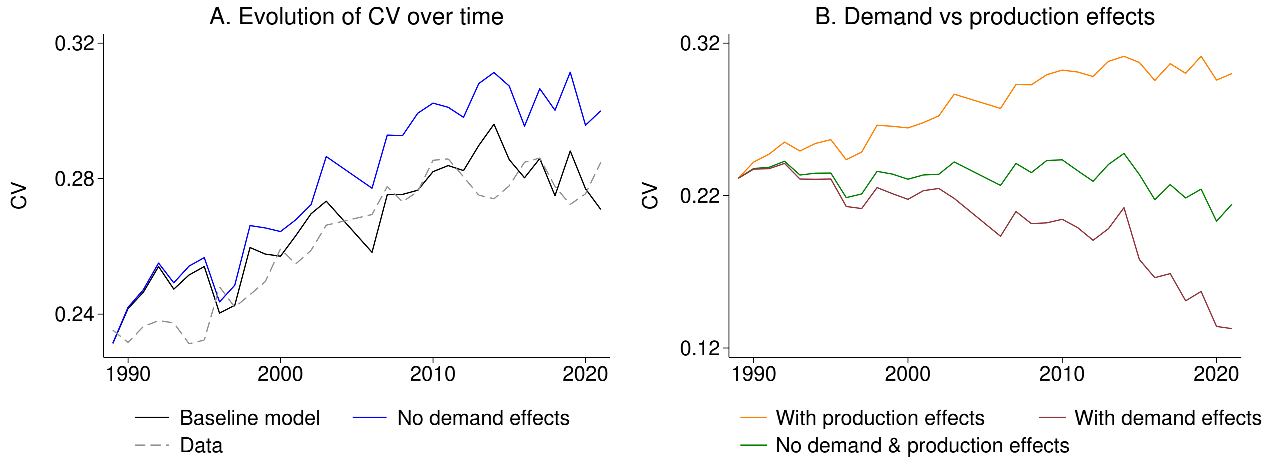

Figure 12: Coefficient of Variation Over Time in the Baseline Model and Counterfactuals

Note: Coefficient of variation, CV, is calculated as in Figure 2. In Panel A, "Data" replicates the CV from Figure 2, "Baseline" plots the CV from the model based on estimates from Tables 2, 3, and 4, and "No demand effects" plots the CV in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3. In Panel B, "With demand effects" plots the CV from a counterfactual that allows DGF effects to change over time while keeping technical progress at the level of 1989. "With production effects" plots the CV from counterfactual that keeps DGF effects constant at the level of 1989 and only allows technical change to occur. "No demand & production effects" is a benchmark that keeps both relative demand and technical progress at the level of 1989. Years 2004-2005 are excluded due to changes in salary reporting in the CEX. See Appendix B for details.

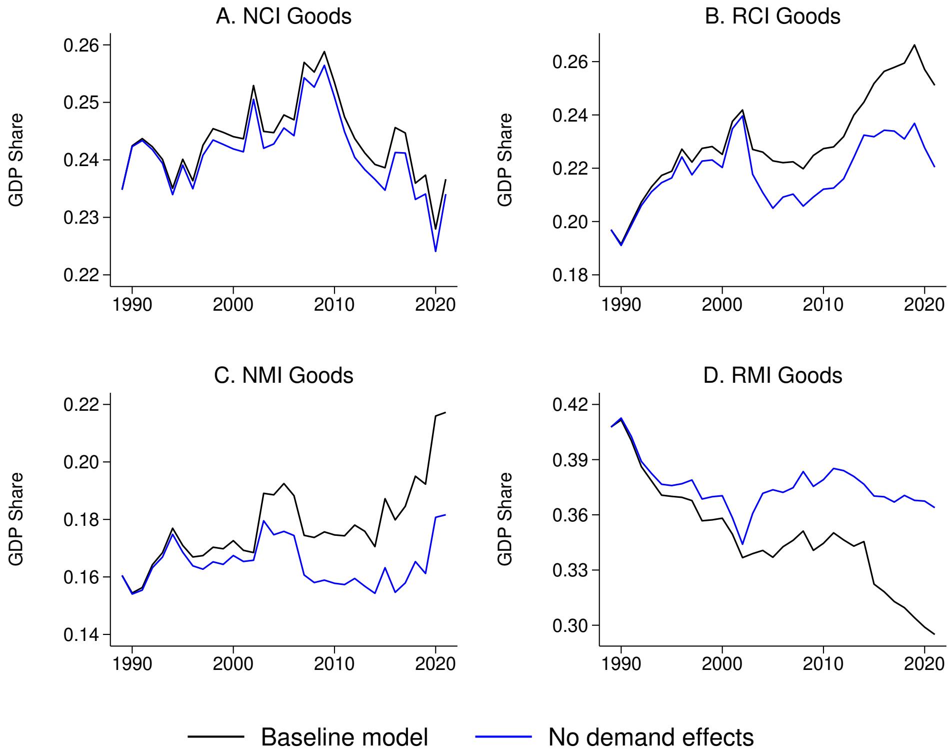

Figure 13: Evolution of Gross Domestic Product Shares Over Time in the Baseline Model and Counterfactual Without Demand Effects

Note: GDP shares are calculated as sectoral value added relative to total value added across all sectors. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. "Baseline" plots GDP shares predicted by the model based on estimates from Tables 2, 3, and 4. "No demand effects"'shows GDP shares in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3.

Table 1: FOCs and Estimated Parameters Under Different Utility Function Specifications

Specification	FOC	Estimated parameters
Non-homothetic CES	$\frac{p_{jt}c_{ijt}}{C_{it}} = \frac{\omega_j p_{jt}^{1-\eta}}{\sum_m \omega_m p_{mt}^{1-\eta}} \left(1 + \sum_m \frac{p_{mt}\bar{c}_{im}}{C_{it}}\right) - \frac{p_{jt}\bar{c}_{ij}}{C_{it}}$	η, ω_j, $\bar{c}_{ij}$
Non-homothetic CES with DGFs	$\frac{p_{jt}c_{ijt}}{C_{it}} = \frac{\omega_j p_{jt}^{1-\eta} e^{\lambda_{ij}t(\eta-1)}}{\sum_m \omega_m p_{mt}^{1-\eta} e^{\lambda_{im}t(\eta-1)}} \left(1 + \sum_m \frac{p_{mt}\bar{c}_{im}}{C_{it}}\right) - \frac{p_{jt}\bar{c}_{ij}}{C_{it}}$	η, ω_j, $\bar{c}_{ij}$, λ_{ij}

Note: The non-homothetic CES specification follows Herrendorf et al. (2013). The non-homothetic CES with Demand Growth Factors (DGFs) introduces time-varying demand shifters that arise through demand growth rates, λ_{ij}. DGFs are expressed by $e^{\lambda_{ij}t}$. For both specifications, i denotes household – nc, rc, nm, rm, and j denotes good – NCI, RCI, NMI, RMI. ω_j's are good-specific non-negative utility weights, η is the elasticity parameter common across households and goods, $\bar{c}_{ij}$ are household-good specific non-homotheticity parameters, and C_{it} is household i's total expenditure at time t. Prices are denoted by p_{jt} and c_{ijt} is houshold i's consumption of goof j at time t.

Table 2: Non-Homothetic CES Estimates Under Different Utility Specifications for the Aggregate Economy

Specification	CEX(1989-2021) No DGFs (1)	CEX(1989-2021) With DGFs (2)	NIPA(1960-2023) No DGFs (3)	NIPA(1960-2023) With DGFs (4)
	Panel A: Elasticity			
η	3.446***	2.700***	1.572***	1.458***
	(0.398)	(0.502)	(0.054)	(0.092)
	Panel B: Utility weights			
ω_{NCI}	0.217***	0.236***	0.203***	0.153***
	(0.012)	(0.016)	(0.003)	(0.004)
ω_{RCI}	0.355***	0.175***	0.274***	0.254***
	(0.024)	(0.023)	(0.009)	(0.007)
ω_{NMI}	0.190***	0.136***	0.116***	0.097***
	(0.010)	(0.014)	(0.003)	(0.005)
ω_{RMI}	0.238***	0.453***	0.407***	0.504***
	(0.013)	(0.031)	(0.009)	(0.009)
	Panel C: Non-homotheticity terms/Subsistence levels			
$\bar{c}_{NCI}$	-1,144.851***	-767.284***	-264.973*	-597.837***
	(23.805)	(69.410)	(159.118)	(38.669)
$\bar{c}_{RCI}$	-957.640***	-647.045***	-377.566*	-842.989***
	(22.310)	(54.289)	(213.090)	(57.285)
$\bar{c}_{NMI}$	-834.385***	-505.372***	-422.114***	-623.119***
	(23.488)	(58.994)	(93.186)	(32.130)
$\bar{c}_{RMI}$	-1,730.663***	-1,238.245***	-1,501.289***	-2,308.967***
	(29.384)	(85.202)	(323.636)	(99.126)
	Panel D: Annual demand growth rates			
λ_{NCI}		0.092***		0.055***
		(0.005)		(0.001)
λ_{RCI}		0.110***		0.062***
		(0.007)		(0.002)
λ_{NMI}		0.112***		0.066***
		(0.009)		(0.005)
λ_{RMI}		0.063***		-0.009
		(0.007)		(0.012)
$RMSE\ E_{NCI}$	0.019	0.012	0.003	0.003
$RMSE\ E_{RCI}$	0.018	0.015	0.009	0.009
$RMSE\ E_{NMI}$	0.015	0.016	0.008	0.008
AIC	-2,233.609	-2,327.648	-1,304.772	-1,491.348
N	132	132	64	64

Note: Estimates are obtained from a demand system consisting of FOCs for three expenditure shares – non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), and non-routine manual intensive (NMI) good shares using non-linear iterated FGLS, as described in Section 4.1. Equation for expenditure share of routine manual intensive (RMI) good was dropped to avoid a singular error covariance matrix. The estimated FOCs for each utility function specification are in Table 1. In columns (1) and (2), estimates are based on the aggregated expenditure data at the quarter-year level from CEX over the period 1989-2021. In columns (3) and (4), estimates are based on the yearly aggregate expenditure data from NIPAs over the period 1960-2023. $RMSE\ E_j$ is the root mean square error for equation for good j. AIC is the Akaike Information Criterion. Standard errors are in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 3: Non-homotheticity and Demand Growth Rate Estimates By Household

Household	Non-routine cognitive (1)	Routine cognitive (2)	Non-routine manual (3)	Routine manual (4)
	Panel A: Non-homotheticity terms/Subsistence levels			
$\bar{c}_{NCI}$	-518.500***	-165.800***	-37.290***	-45.170***
	(19.020)	(5.635)	(3.161)	(2.469)
$\bar{c}_{RCI}$	-360.100***	-136.400***	-36.710***	-51.120***
	(13.060)	(4.833)	(2.935)	(4.261)
$\bar{c}_{NMI}$	-333.200***	-105.000***	-15.860***	-28.700***
	(15.400)	(5.761)	(3.291)	(4.125)
$\bar{c}_{RMI}$	-715.800***	-272.400***	-89.530***	-120.400***
	(27.190)	(8.897)	(4.481)	(3.839)
	Panel B: Annual demand growth rates			
λ_{NCI}	0.097***	0.104***	0.083***	0.013
	(0.002)	(0.003)	(0.003)	(0.064)
λ_{RCI}	0.117***	0.130***	0.102***	0.041
	(0.003)	(0.003)	(0.005)	(0.065)
λ_{NMI}	0.117***	0.128***	0.103***	0.024
	(0.003)	(0.003)	(0.004)	(0.069)
λ_{RMI}	0.064***	0.079***	0.059***	0.000
	(0.002)	(0.002)	(0.003)	(0.062)

Note: Estimates are obtained using quarter-year household-level aggregated data from a demand system for three expenditure shares – non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), and non-routine manual intensive (NMI) good shares, given by equation 11. All equations are estimated jointly for a sample with 528 quarter-year-household observations. Equation for expenditure share of routine manual intensive (RMI) good was dropped to avoid a singular error covariance matrix. Estimation is done using non-linear iterated FGLS, as described in Section 4.1. The elasticity, η, and utility weights, ω's, were taken from the aggregate economy estimates, reported in Table 2 column(2). Standard errors are in parentheses.
* p<0.10 ** p<0.05 *** p<0.01.

Table 4: Relative Size of Non-Homotheticity Terms and Demand Growth Rates by Household

Household	Non-routine cognitive (1)	Routine cognitive (2)	Non-routine manual (3)	Routine manual (4)
	Panel A: Subsistence relative to average consumption			
$\bar{c}_{NCI}/c_{NCI}$	-0.686***	-0.611***	-0.410***	-0.459***
	(0.028)	(0.023)	(0.036)	(0.028)
$\bar{c}_{RCI}/c_{RCI}$	-0.619***	-0.576***	-0.461***	-0.502***
	(0.026)	(0.022)	(0.038)	(0.044)
$\bar{c}_{NMI}/c_{NMI}$	-0.590***	-0.512***	-0.240***	-0.375***
	(0.031)	(0.030)	(0.050)	(0.055)
$\bar{c}_{RMI}/c_{RMI}$	-0.688***	-0.625***	-0.540***	-0.588***
	(0.029)	(0.022)	(0.029)	(0.024)
	Panel B: Differences in the demand growth rates			
λ_{RCI} - λ_{NCI}	0.020***	0.025***	0.019***	0.028***
	(0.001)	(0.001)	(0.002)	(0.003)
λ_{NMI} - λ_{NCI}	0.024***	0.019***	0.023***	0.012**
	(0.001)	(0.001)	(0.002)	(0.006)
λ_{RMI} - λ_{NCI}	-0.033***	-0.025***	-0.025***	-0.012***
	(0.002)	(0.001)	(0.002)	(0.003)

Note: Panels A and B are based on estimates from Table 3. NCI – non-routine cognitive intensive good, RCI – routine cognitive intensive good, NMI – non-routine manual intensive good, and RMI – routine manual intensive good. Standard errors are in parentheses. Standard errors for $\bar{c}_j/c_j$ are obtained using Delta method approximation. * p<0.10 ** p<0.05 *** p<0.01.

Table 5: Production Elasticities and Technical Growth Rate Estimates by Sector

Sector	Non-routine cognitive intensive NCI (1)	Routine cognitive intensive RCI (2)	Non-routine manual intensive NMI (3)	Routine manual intensive RMI (4)
Panel A: Factor Augmenting Annual Technical Growth Rates				
γ_{Lnc}	0.006***	0.001*	0.011***	0.008**
	(0.001)	(0.000)	(0.000)	(0.003)
γ_{Lrc}	-0.022***	-0.033***	-0.020***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.002)
γ_{Lnm}	-0.013***	-0.020***	-0.011***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
γ_{Lrm}	-0.034***	-0.014***	-0.012***	-0.014***
	(0.002)	(0.001)	(0.001)	(0.001)
γ_K	-0.025***	-0.005***	0.004***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Production Elasticities				
σ	1.362***	1.532***	1.552***	1.187***
	(0.008)	(0.010)	(0.016)	(0.007)
σ_{Lnc}	2.011***	1.618***	1.691***	1.068***
	(0.042)	(0.014)	(0.020)	(0.003)
σ_{Lrc}	1.526***	1.332***	1.604***	1.827***
	(0.023)	(0.008)	(0.022)	(0.044)
σ_{Lnm}	1.997***	1.969***	1.570***	1.483***
	(0.049)	(0.031)	(0.023)	(0.034)
σ_{Lrm}	1.599***	2.329***	1.794***	1.870***
	(0.034)	(0.059)	(0.038)	(0.062)
σ_K	1.229***	1.493***	1.443***	1.493***
	(0.005)	(0.010)	(0.013)	(0.023)

Note: Estimates are from the system of 24 equations, given by equations 13-15 for each sector. Sample and data construction follow Figure 1, where expenditures are mapped to costs on labour and capital for the four sectors – NCI, RCI, NMI, and RMI, as discussed in Section 2. All equations are estimated jointly for a sample with 528 quarter-year-sector observations. Estimation is done using non-linear 3SLS, as described in Section 4.2. L_{nc} is non-routine cognitive labour, L_{rc} – routine cognitive labour, L_{nm} –non-routine manual labour, L_{rm} – routine manual labour, and K – capital. Standard errors are in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 6: Sector-Specific Annual Output Growth Rates

Sector	Non-routine cognitive intensive NCI (1)	Routine cognitive intensive RCI (2)	Non-routine manual intensive NMI (3)	Routine manual intensive RMI (4)
	Panel A: Annual output growth rate			
δ_j	0.003	0.012***	0.010***	0.006**
	(0.003)	(0.002)	(0.003)	(0.002)
	Panel B: Output growth rate compared to average			
$\overline{\delta}$	0.008			
$\delta_j - \overline{\delta}$	-0.005	0.004	0.002	-0.002
N	132	132	132	132

Note: Estimates are based on OLS regressions given by $log(c_{jt}) = \beta + \delta t + e_{jt}$, where $log(c_{jt})$ is the log of total output of good j and t is the trend variable. $\delta_j - \overline{\delta}$ show the difference between sector specific annual growth rates and the average output growth rate. Estimation is based on quarter-year data, as described in Section 2. Standard errors are in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Table 7: Changes in Coefficient of Variation in Baseline Model and Counterfactual Without Demand Effects

CV	1989 (1)	2021 (2)	Δ (3)	Δ relative to benchmark (4)
	Panel A: Evolution of CV over time			
Data	0.235	0.285	0.050	
Baseline model (benchmark)	0.231	0.271	0.040	
No demand effects	0.231	0.300	0.069	0.029 (173%)
	Panel B: Demand vs production effects			
No demand and production effects (benchmark)	0.231	0.214	-0.017	
With demand effects only	0.231	0.133	-0.098	-0.081 (577%)
With production effects only	0.231	0.300	0.069	0.086 (-665%)

Note: In Panel A, "Data" reports the CV from Figure 2, "Baseline model" reports the CV from the model based on estimates from Tables 2, 3, and 4, and "No demand effects" reports the CV in the counterfactual when setting DGFs to be at the level of 1989 for all years, as discussed in Section 4.3. In Panel B, "With demand effects" reports the CV from a counterfactual that allows DGF effects to change over time while keeping technical progress at the level of 1989. "With production effects" reports the CV from counterfactual that keeps DGF effects constant at the level of 1989 and only allows technical change to occur. "No demand & production effects" is a benchmark that keeps both relative demand and technical progress at the level of 1989.

Appendix A: Supplementary Figures and Tables

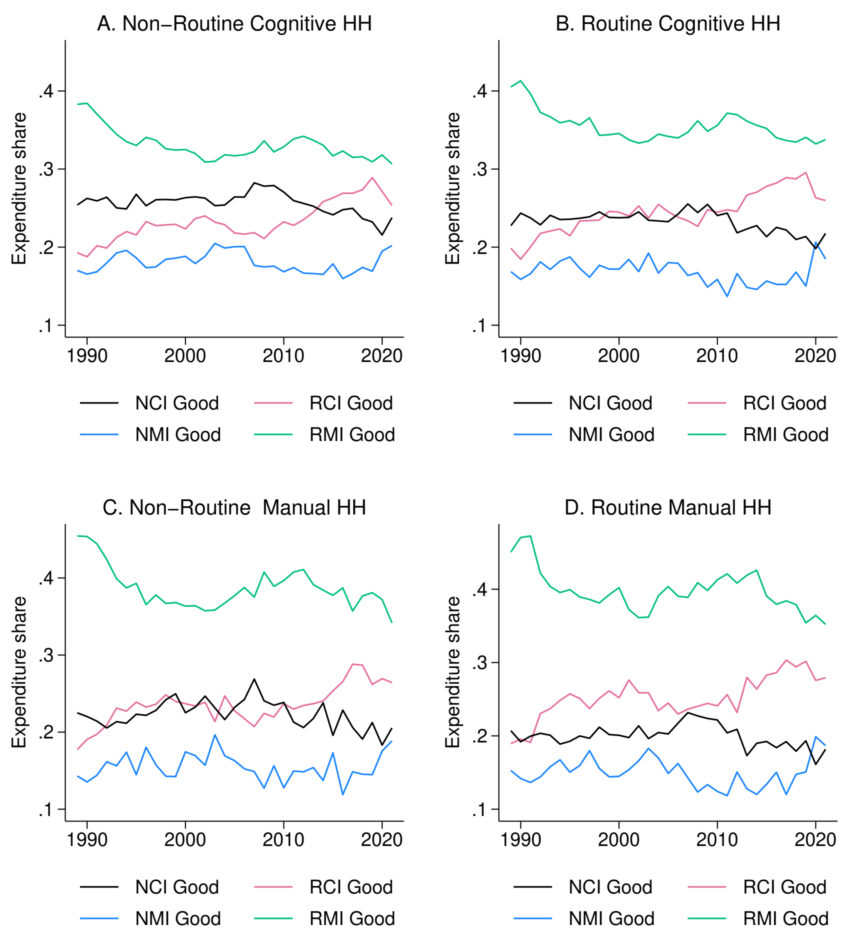

Figure A.1: Expenditure shares by Good Type Across Households

Note: HH – household. NCI – non-routine cognitive good; RCI - routine cognitive intensive good; NMI – non-routine manual intensive good; RMI – routine manual intensive good.

Data Fit Figures from Household's and Sector's Problems

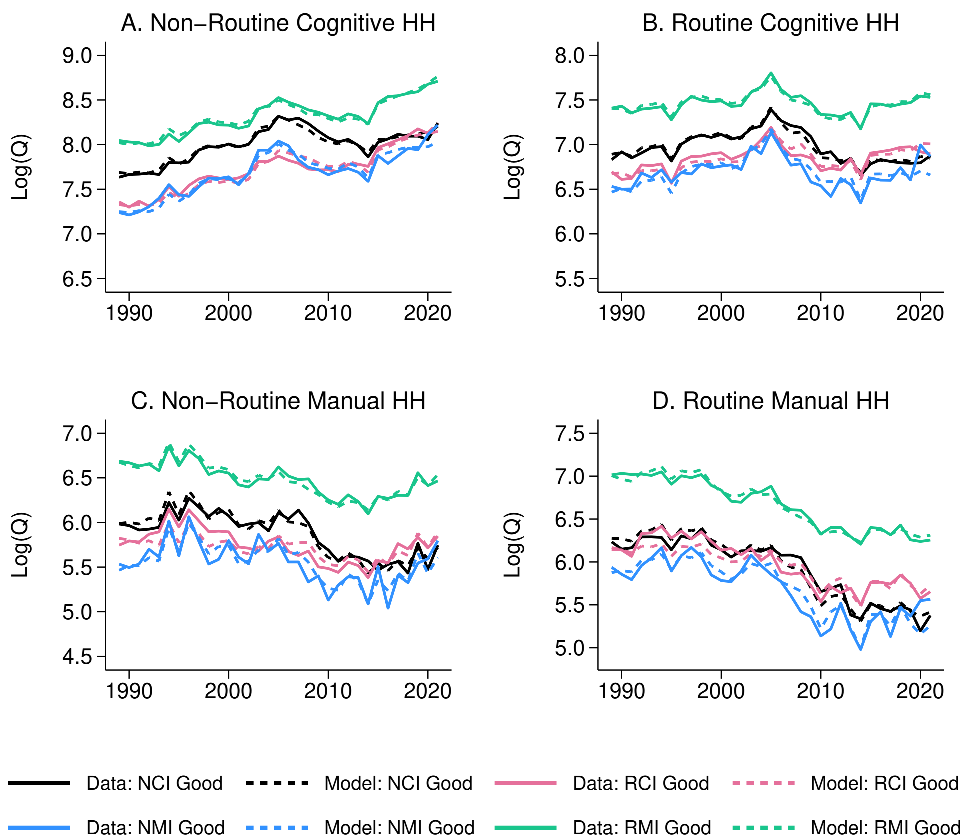

Figure A.2: Fit of Log Quantities Consumed by Households

Note: HH - household. Estimates are obtained using quarter-year household-level aggregated data from a demand system for three expenditure shares – non-routine cognitive intensive, routine cognitive intensive, and routine manual intensive good shares, given by equation 11. Equation for expenditure share of routine manual intensive good was dropped to avoid a singular error covariance matrix. Estimation is done using iterated FGLS. The elasticity, η, and utility weights, ω's, were taken from the aggregate economy estimates, reported in Table 2 column(2). Estimates used to get fitted shares are obtained using aggregated data at the quarter-year level and are reported in Tables 2 and 3.

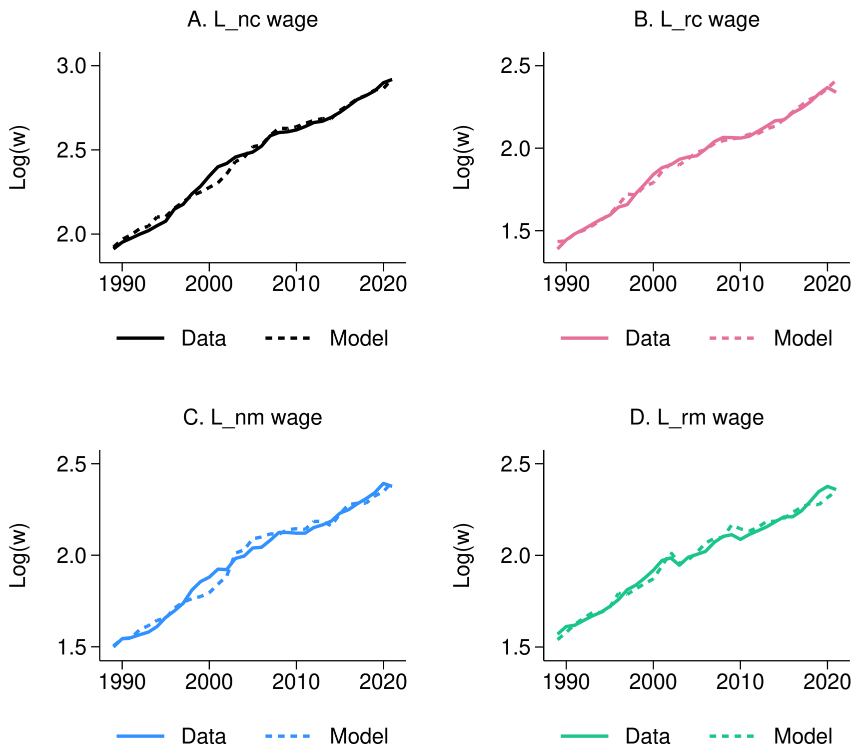

Figure A.3: Wages for Non-Routine Cognitive Intensive (NCI) Sector by Labour Type

Note: Fitted values are based on estimates reported in Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

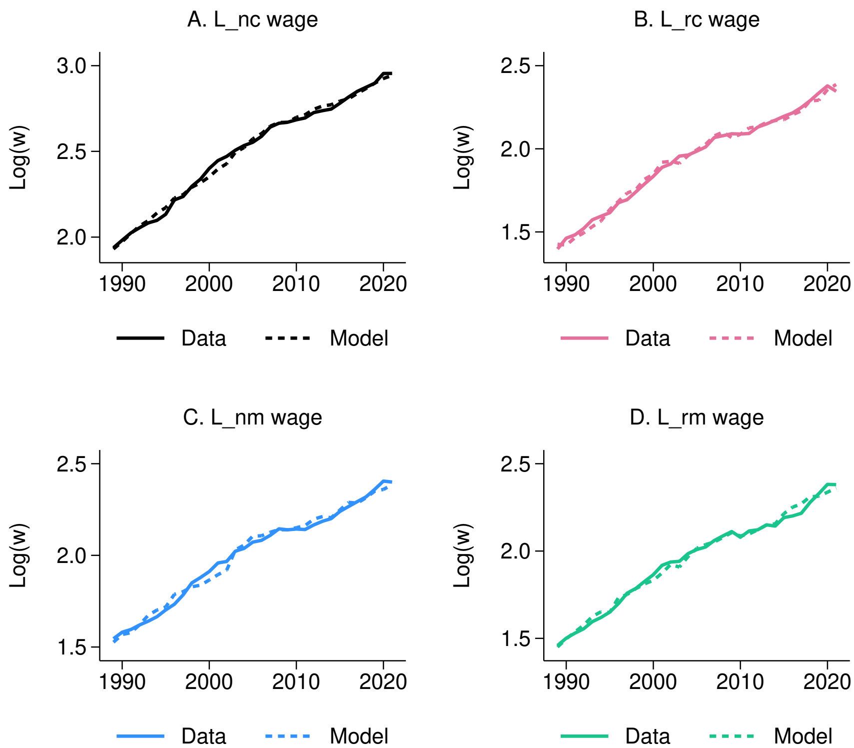

Figure A.4: Wages for Routine Cognitive Intensive (RCI) Sector by Labour Type

Note: Fitted values are based on estimates reported in Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

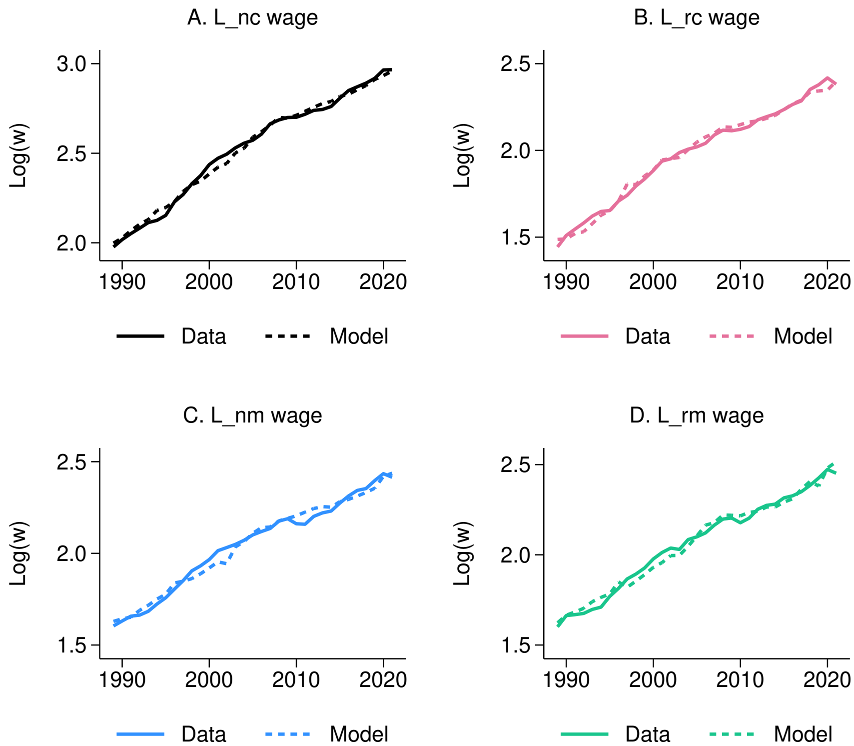

Figure A.5: Wages for Non-Routine Manual Intensive (NMI) Sector by Labour Type

Note: Fitted values are based on estimates reported in Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

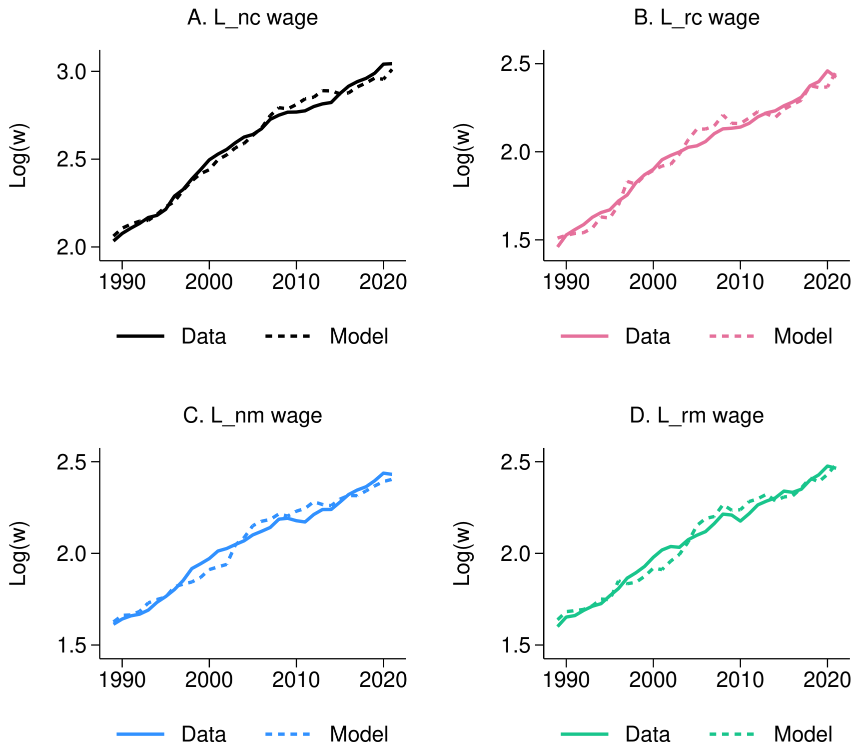

Figure A.6: Wages for Routine Manual Intensive (RMI) Sector by Labour Type

Note: Fitted values are based on estimates reported in Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

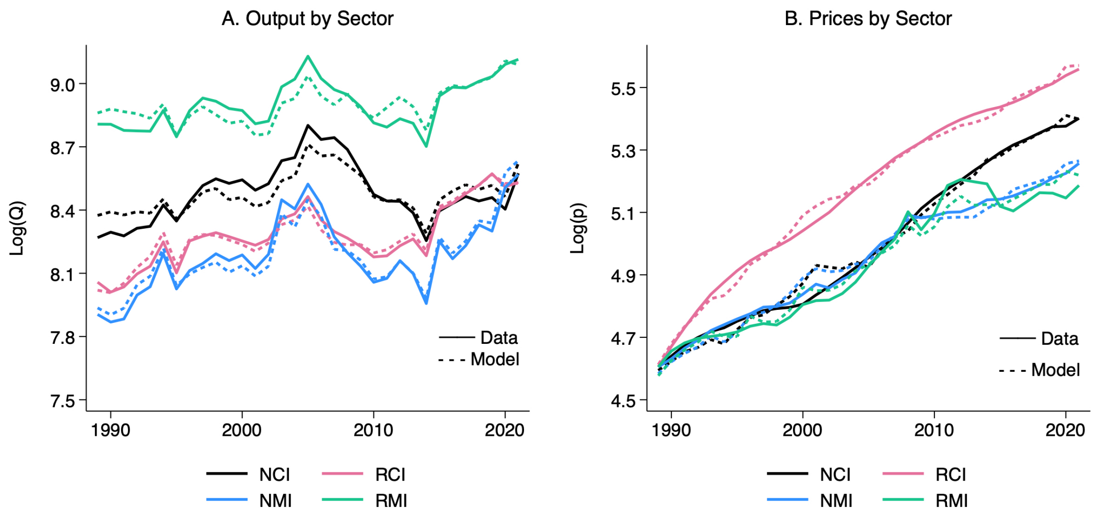

Figure A.7: Output and Prices by Sector

Note: Fitted values are based on estimates reported in Table 4. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector.

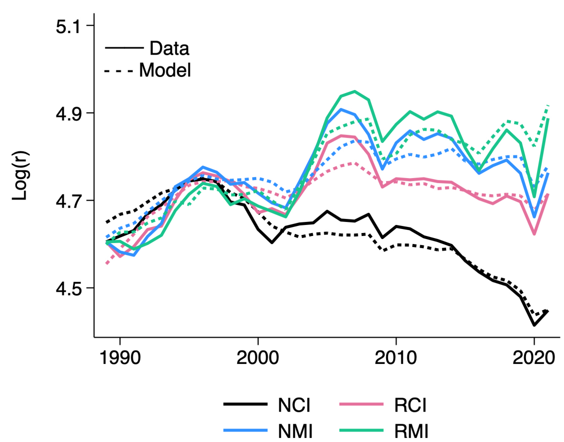

Figure A.8: Rent by Sector

Note: Fitted values are based on estimates reported in Table 4. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector.

Supplementary Tables for Sector's Problem

Table A.1: Allen-Uzawa Factor-Pair Elasticities of Substitution by Sector

Sector	Non-routine cognitive intensive NCI (1)	Routine cognitive intensive RCI (2)	Non-routine manual intensive NMI (3)	Routine manual intensive RMI (4)
$\rho_{K\ L_{nc}}$	1.581***	1.523***	1.556***	1.116***
	(0.019)	(0.011)	(0.015)	(0.012)
$\rho_{K\ L_{rc}}$	1.199***	1.254***	1.475***	1.909***
	(0.019)	(0.011)	(0.020)	(0.047)
$\rho_{K\ L_{nm}}$	1.570***	1.854***	1.445***	1.550***
	(0.032)	(0.025)	(0.019)	(0.030)
$\rho_{K\ L_{rm}}$	1.257***	2.192***	1.650***	1.955***
	(0.027)	(0.051)	(0.031)	(0.057)
$\rho_{L_{nc}\ L_{rc}}$	1.962***	1.359***	1.729***	1.365***
	(0.038)	(0.009)	(0.025)	(0.027)
$\rho_{L_{nc}\ L_{nm}}$	2.568***	2.009***	1.693***	1.109***
	(0.076)	(0.032)	(0.025)	(0.022)
$\rho_{L_{nc}\ L_{rm}}$	2.056***	2.377***	1.934***	1.398***
	(0.049)	(0.057)	(0.040)	(0.038)
$\rho_{L_{rc}\ L_{nm}}$	1.948***	1.653***	1.605***	1.896***
	(0.050)	(0.020)	(0.025)	(0.061)
$\rho_{L_{rc}\ L_{rm}}$	1.559***	1.956***	1.834***	2.391***
	(0.036)	(0.042)	(0.034)	(0.090)
$\rho_{L_{nm}\ L_{rm}}$	2.041***	2.891***	1.796***	1.942***
	(0.072)	(0.089)	(0.044)	(0.077)

Note: Allen-Uzawa elasticities (AES) are calculated based on equation 7 using CRESH elasticity estimates from Table 4 and geometric averages of factor shares. Figure 4 plots AES for the four sectors. Standard errors are in parentheses and are obtained using the Delta method approximation. * $p<0.10$ ** $p<0.05$ *** $p<0.01$.

Table A.2: Elasticities of Substitution and Technical Growth Rate Estimates by Sector Based on CES Production Function

Sector	Non-routine cognitive intensive NCI (1)	Routine cognitive intensive RCI (2)	Non-routine manual intensive NMI (3)	Routine manual intensive RMI (4)
	Panel A: Production Elasticities			
σ_j	1.326***	1.936***	1.616***	1.414***
	(0.001)	(0.007)	(0.003)	(0.002)
	Panel B: Factor Augmenting Annual Technical Growth Rates			
γ_{L1j}	0.016***	0.003***	0.014***	0.011***
	(0.001)	(0.000)	(0.000)	(0.001)
γ_{L2j}	-0.037***	-0.013***	-0.020***	-0.049***
	(0.001)	(0.000)	(0.000)	(0.001)
γ_{L3j}	-0.041***	-0.017***	-0.009***	-0.018***
	(0.001)	(0.000)	(0.001)	(0.001)
γ_{L4j}	-0.063***	-0.013***	-0.015***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.001)
γ_{Kj}	-0.022***	-0.015***	0.002***	0.016***
	(0.000)	(0.000)	(0.000)	(0.001)

Note: Estimates are based on quarter-year data from the system of 24 equations, given by equations 13-15 for each sector, while equating all factor specific σ's for each sector. Estimation is done using non-linear 3SLS, as described in Section 4.2. Standard errors are in parentheses. All equations are estimated jointly for a sample with 528 quarter-year-sector observations. * p<0.10 ** p<0.05 *** p<0.01.

Data Fit Figures from Counterfactual Analysis at the Household Level

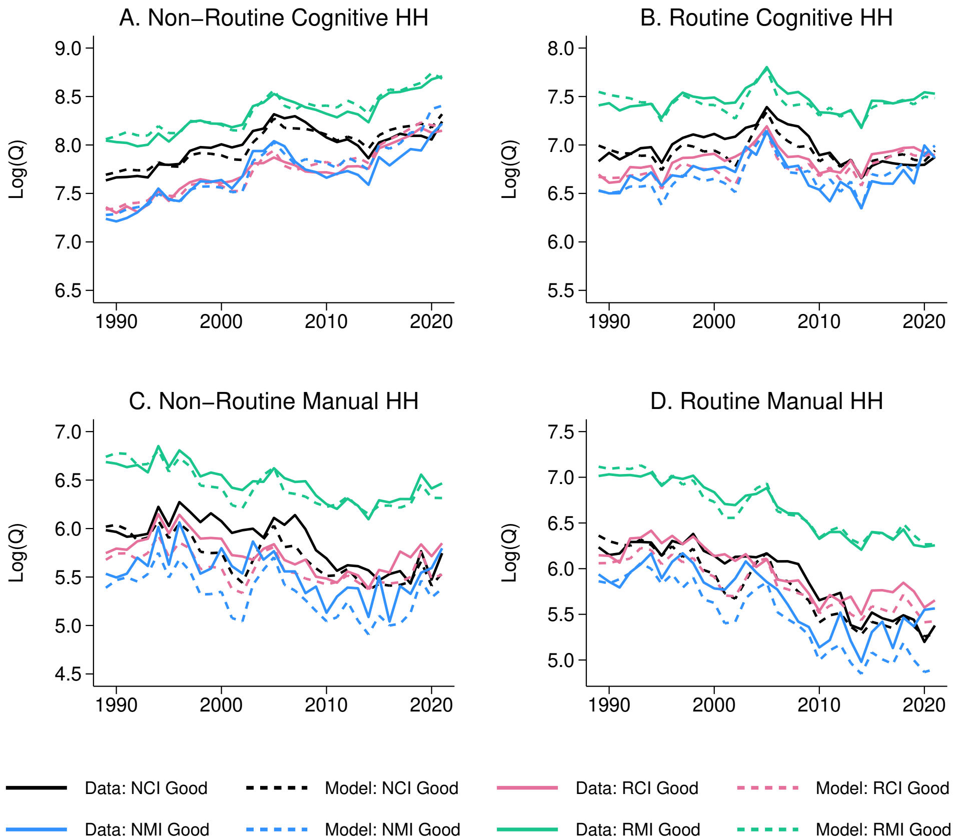

Figure A.9: Household-Level Consumption: Counterfactual Baseline Model Data Fit

Note: HH - household. Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2), 3, and 4.

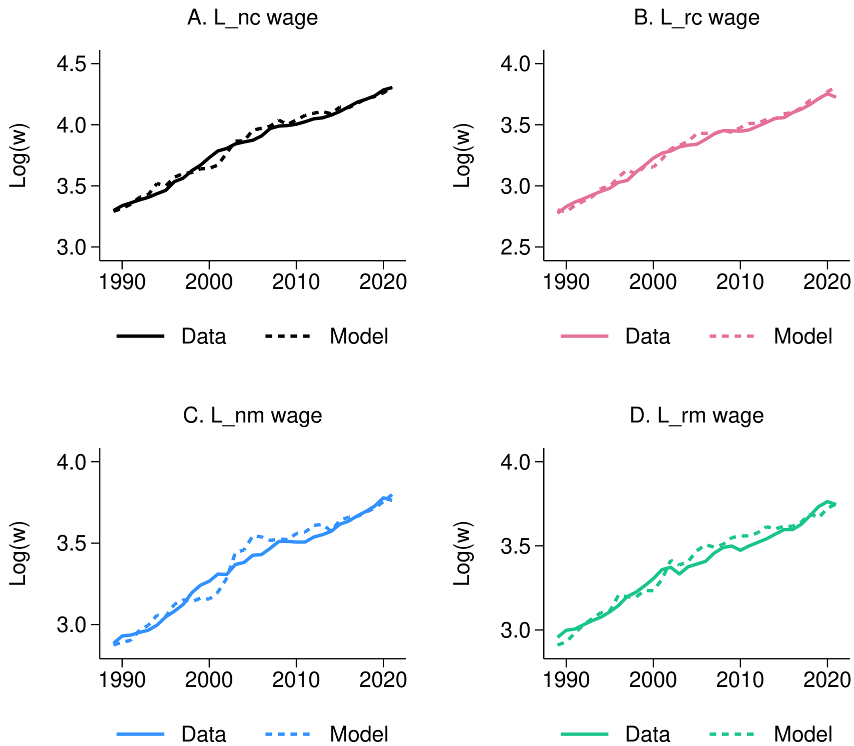

Figure A.10: Wages for Non-Routine Cognitive Intensive (NCI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2), 3, and 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

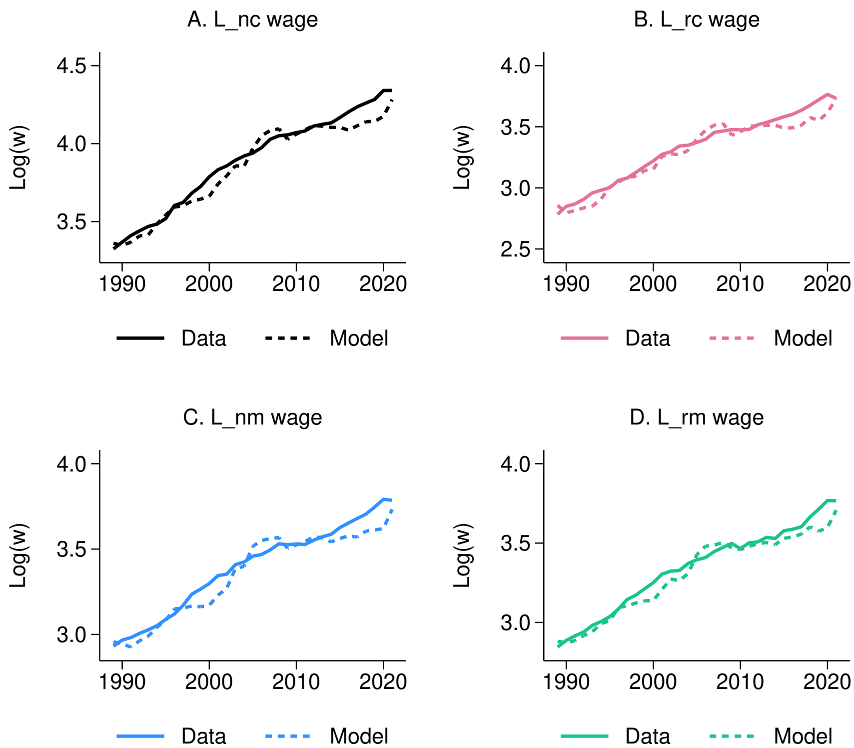

Figure A.11: Wages for Routine Cognitive Intensive (RCI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2), 3, and 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

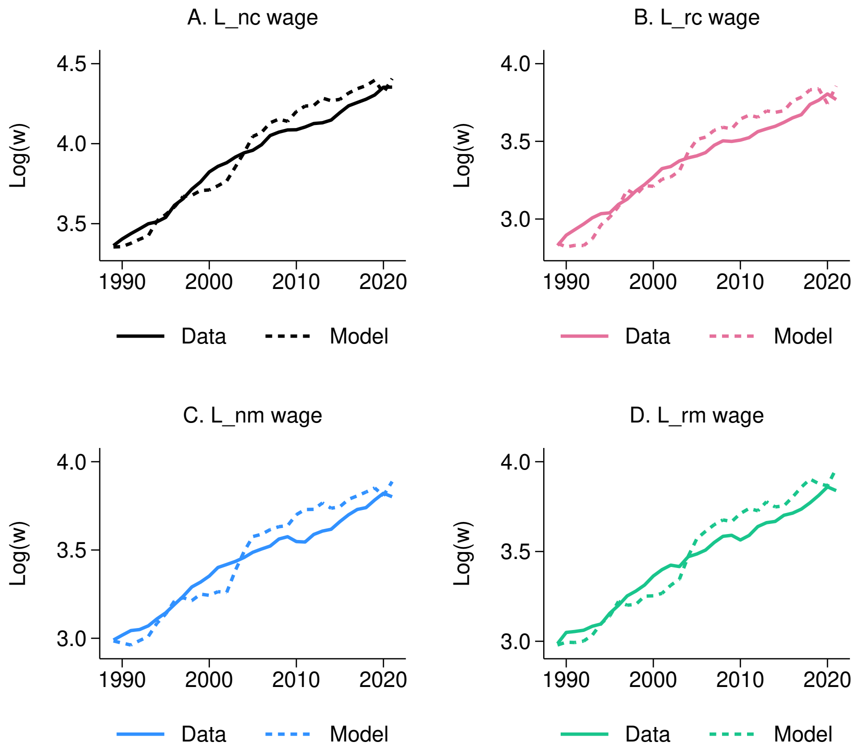

Figure A.12: Wages for Non-Routine Manual Intensive (NMI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2), 3, and 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

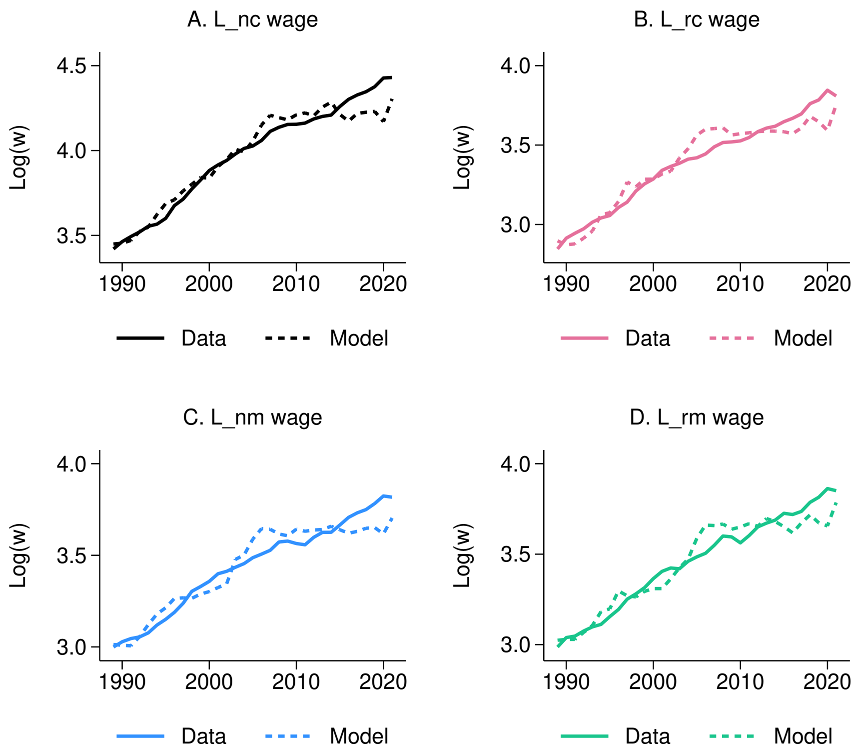

Figure A.13: Wages for Routine Manual Intensive (RMI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

Note: Fitted values are based on estimates reported in Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

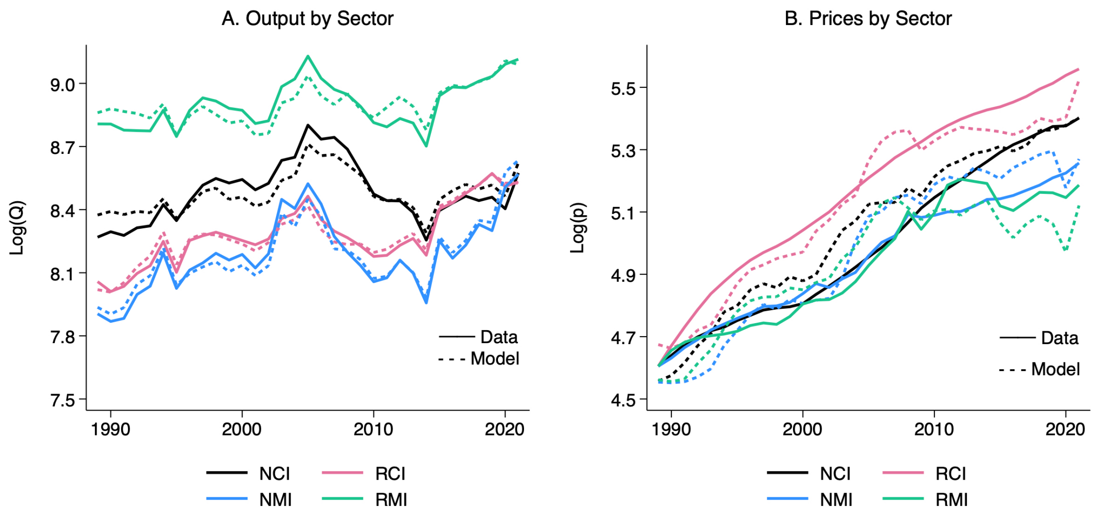

Figure A.14: Output and Prices by Sector

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2), 3, and 4. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector.

Data Fit Figures from Counterfactual Analysis at the Aggregate Economy Level

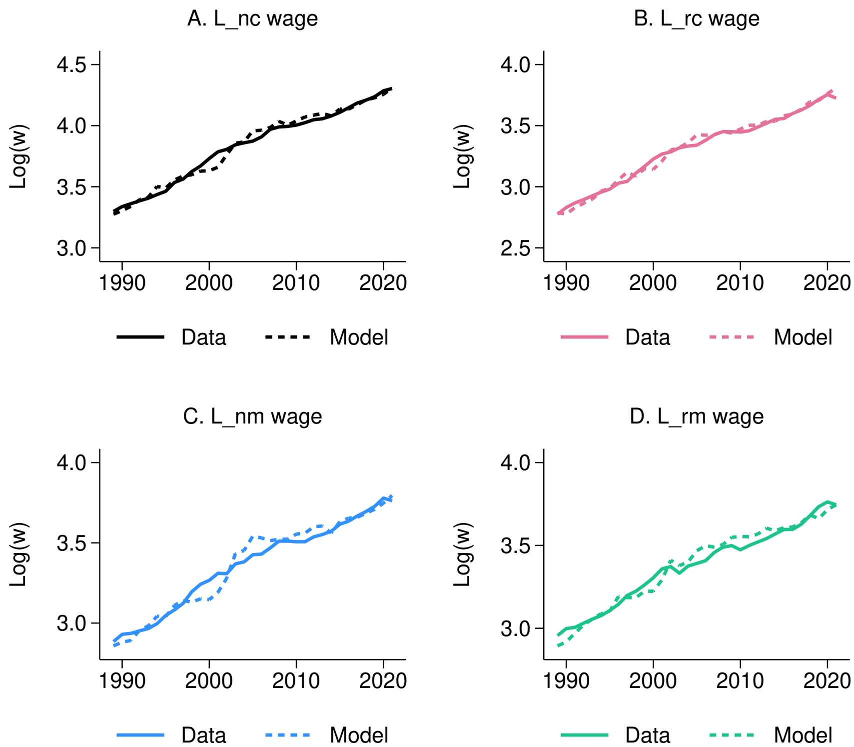

Figure A.15: Wages for Non-Routine Cognitive Intensive (NCI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2) and Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

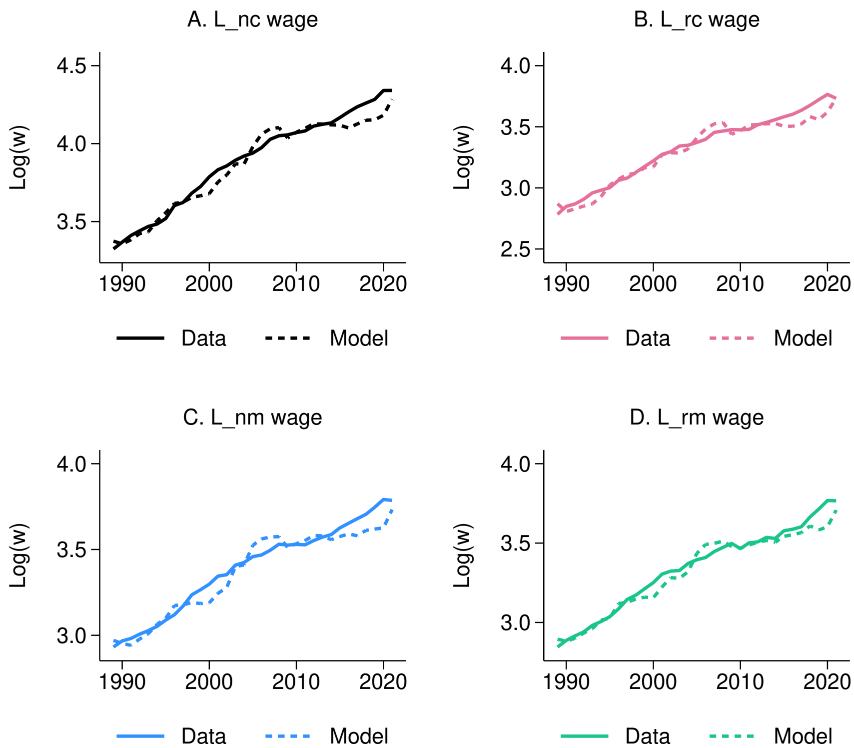

Figure A.16: Wages for Routine Cognitive Intensive (RCI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2) and Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

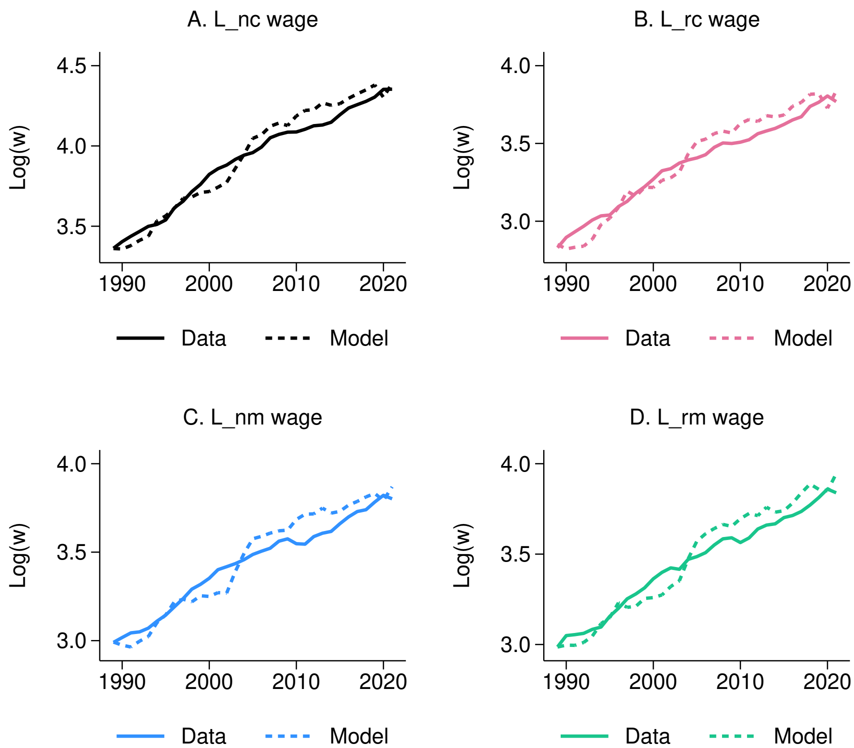

Figure A.17: Wages for Non-Routine Manual Intensive (NMI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2) and Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

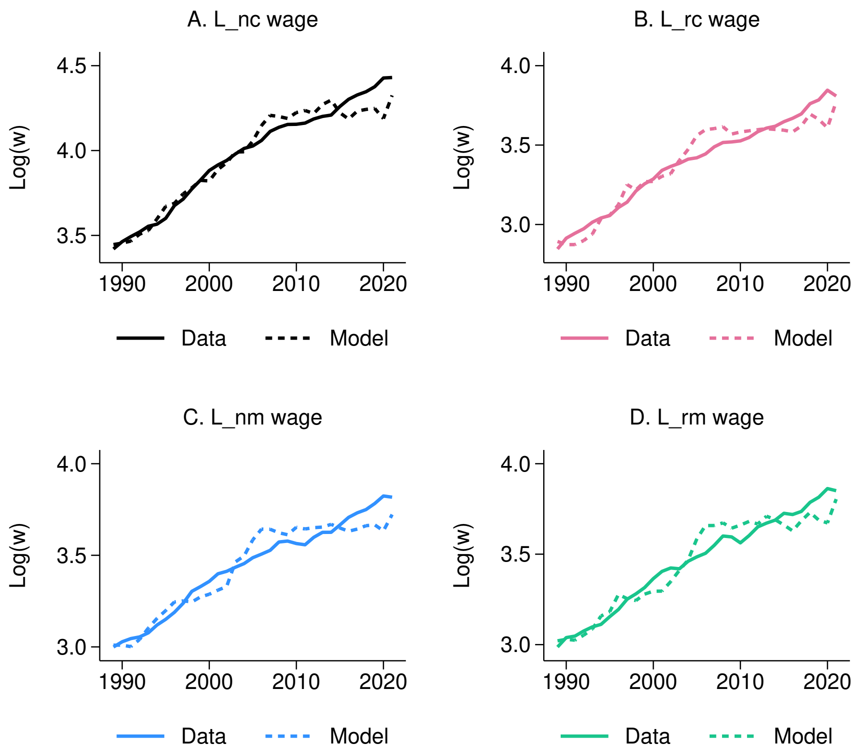

Figure A.18: Wages for Routine Manual Intensive (RMI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

Note: Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2) and Table 4. L_nc is non-routine cognitive labour, L_rc is routine cognitive labour, L_nm is non-routine manual labour, L_rm is routine manual labour.

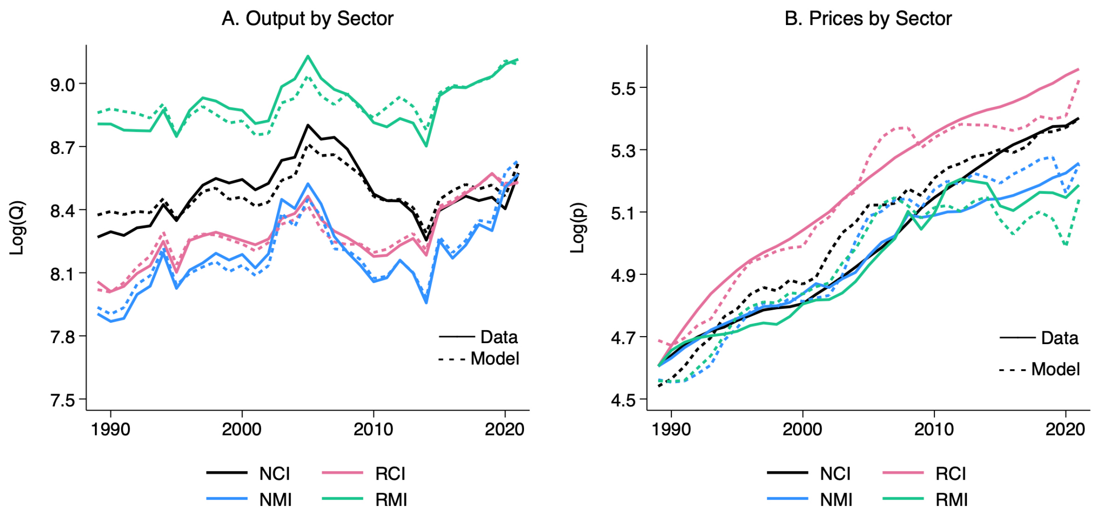

Figure A.19: Output and Prices by Sector: Aggregate Economy Counterfactual Baseline Model Data Fit

Note: In the aggregate economy counterfactuals aggregate consumption is equal to aggregate production. Estimates used to solve for equilibrium in counterfactual analysis are reported in Tables 2 column(2) and Table 4. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector.

Additional Counterfactual Figures

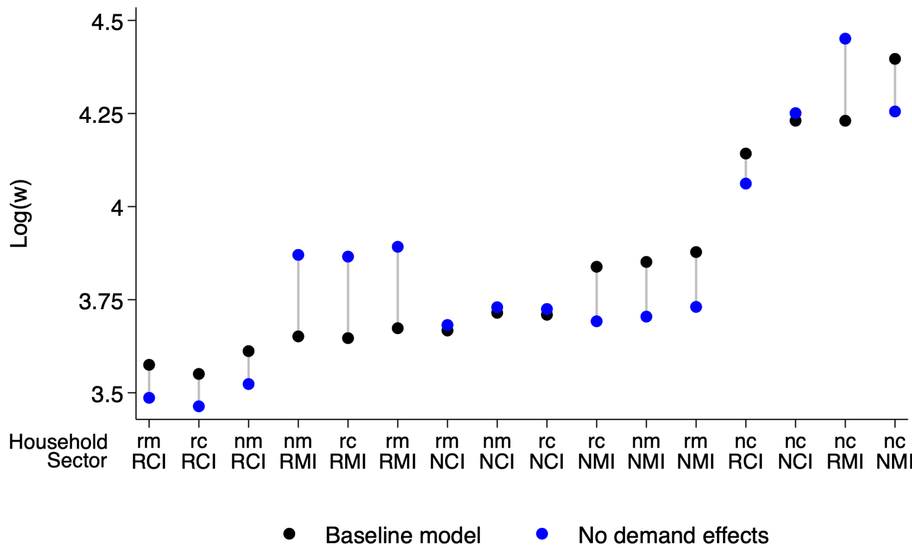

Figure A.20: Wages In the Baseline Model and Counterfactual Without Demand Effects in 2019

Note: Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

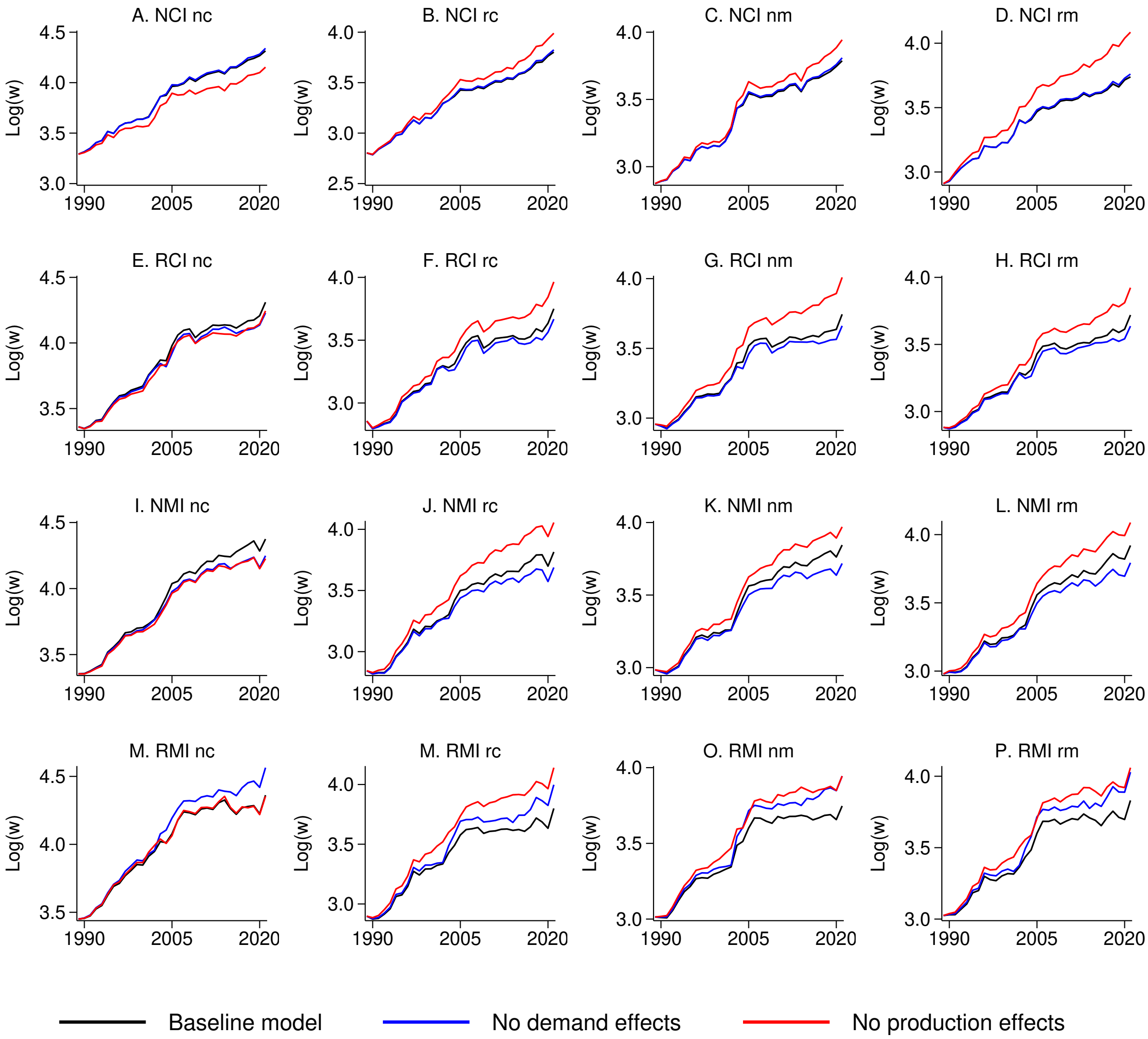

Figure A.21: Wage Counterfactuals Over Time with Constant Household Distribution

Note: Baseline model and counterfactual with constant household distribution solve for equilibrium allocations and prices when keeping keeping household shares at the level of 1989 for all years. Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

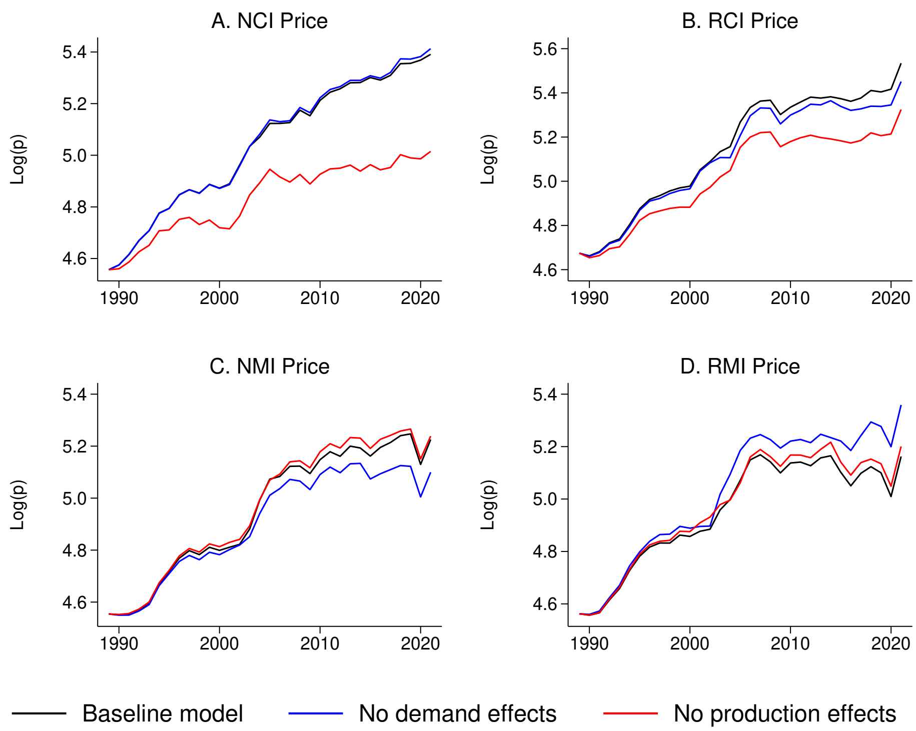

Figure A.22: Price Counterfactuals Over Time with Constant Household Distribution

Note: Baseline model and counterfactual with constant household distribution solve for equilibrium allocations and prices when keeping keeping household shares at the level of 1989 for all years. Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

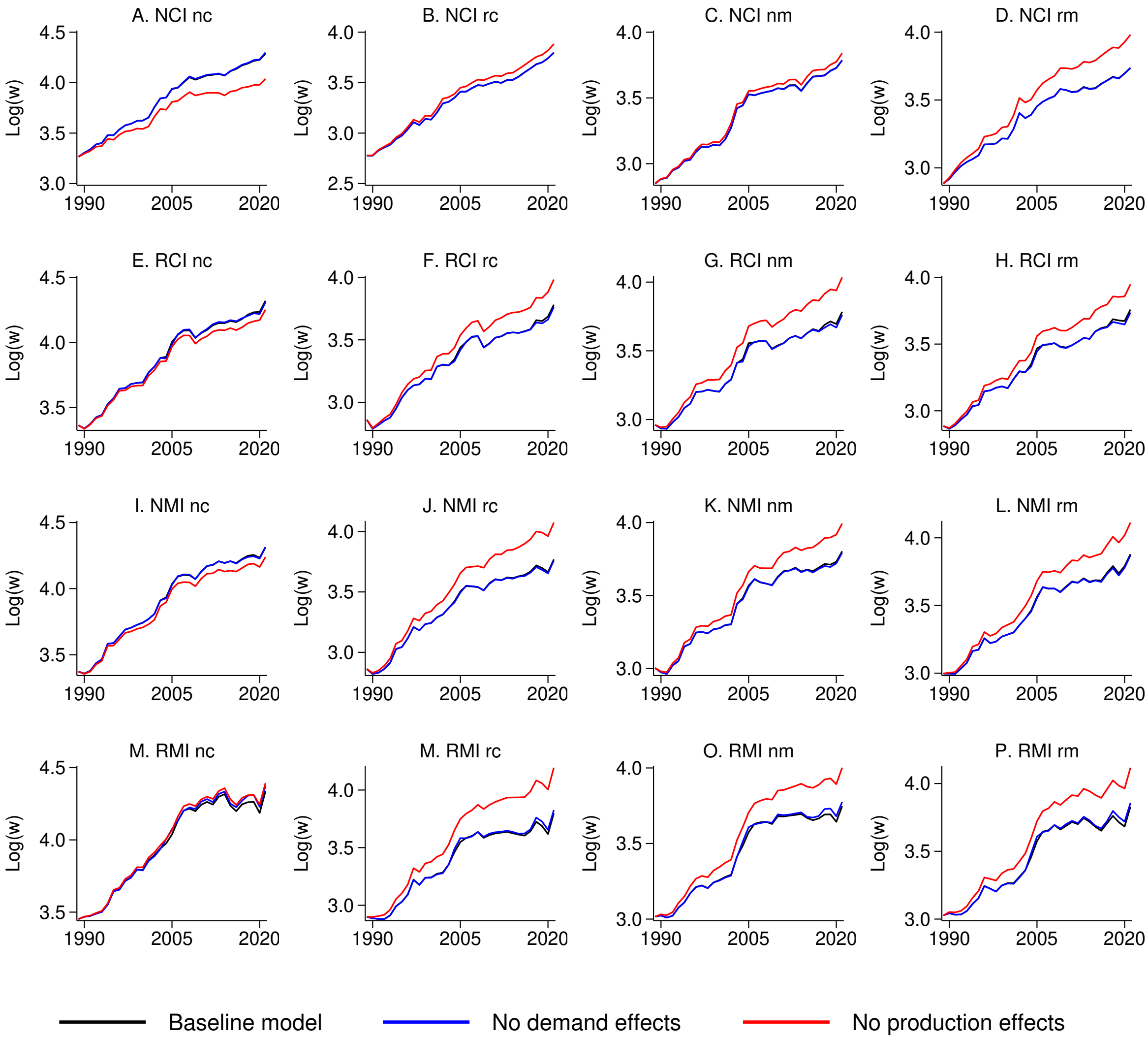

Figure A.23: Wage Counterfactuals Over Time for $\eta = 0$

Note: Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

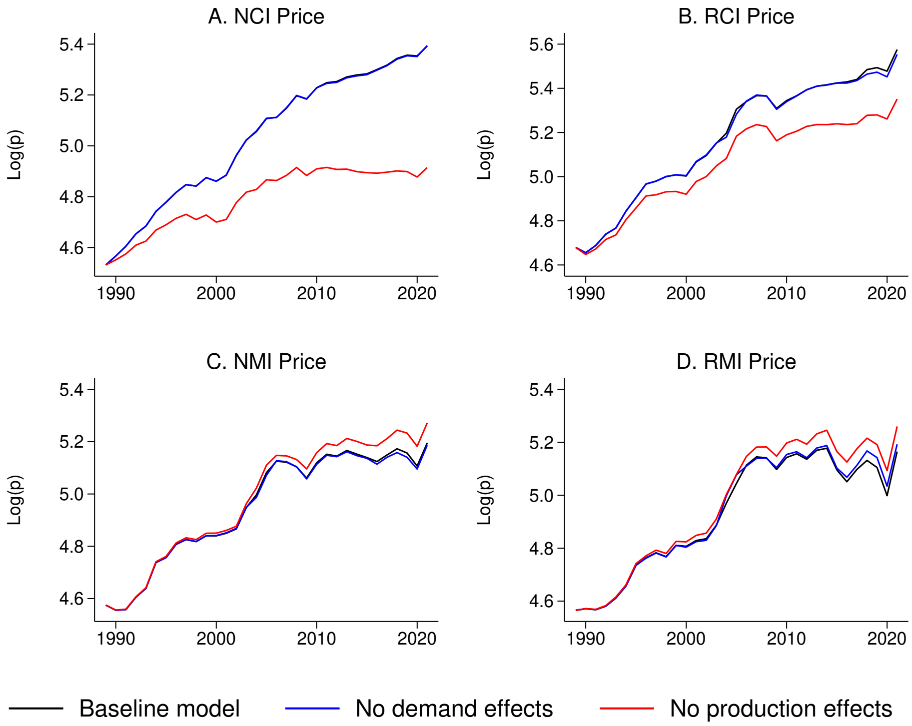

Figure A.24: Price Counterfactuals Over Time for $\eta = 0$

Note: Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

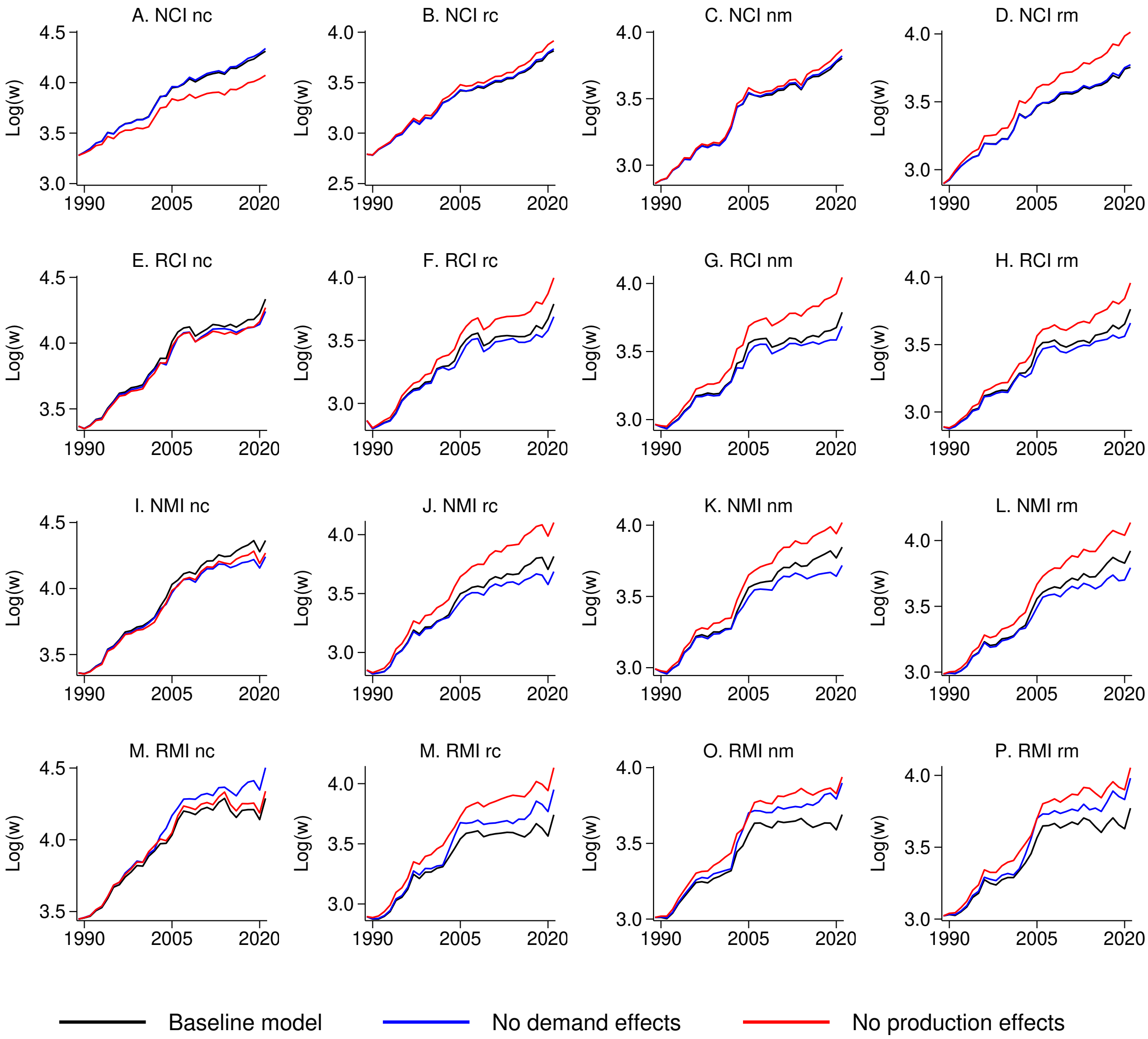

Figure A.25: Wage Counterfactuals Over Time for $\eta = 1.5$

Note: Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

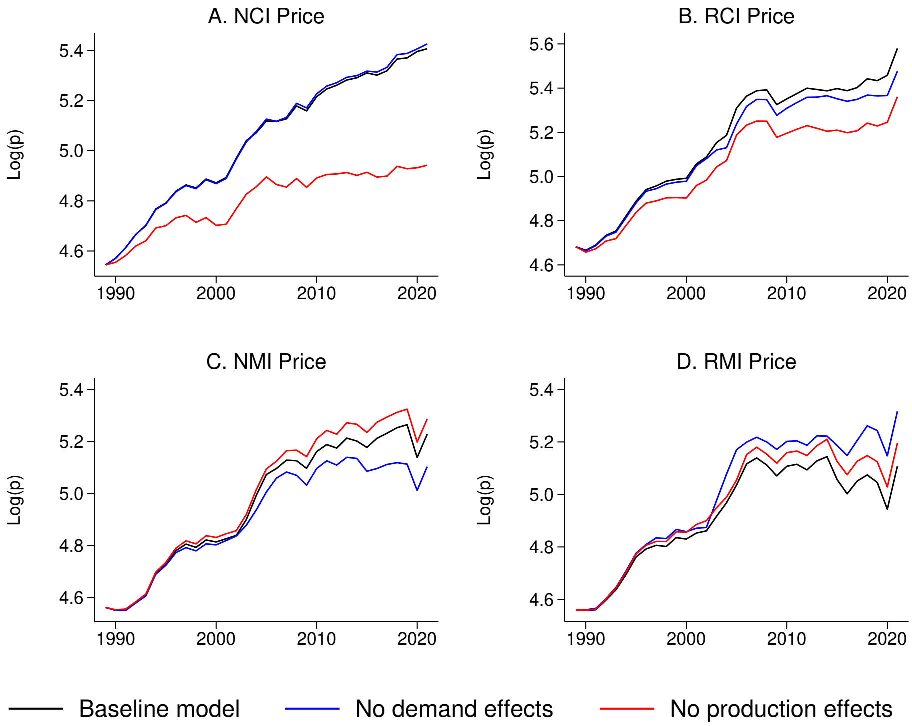

Figure A.26: Price Counterfactuals Over Time for $\eta = 1.5$

Note: Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

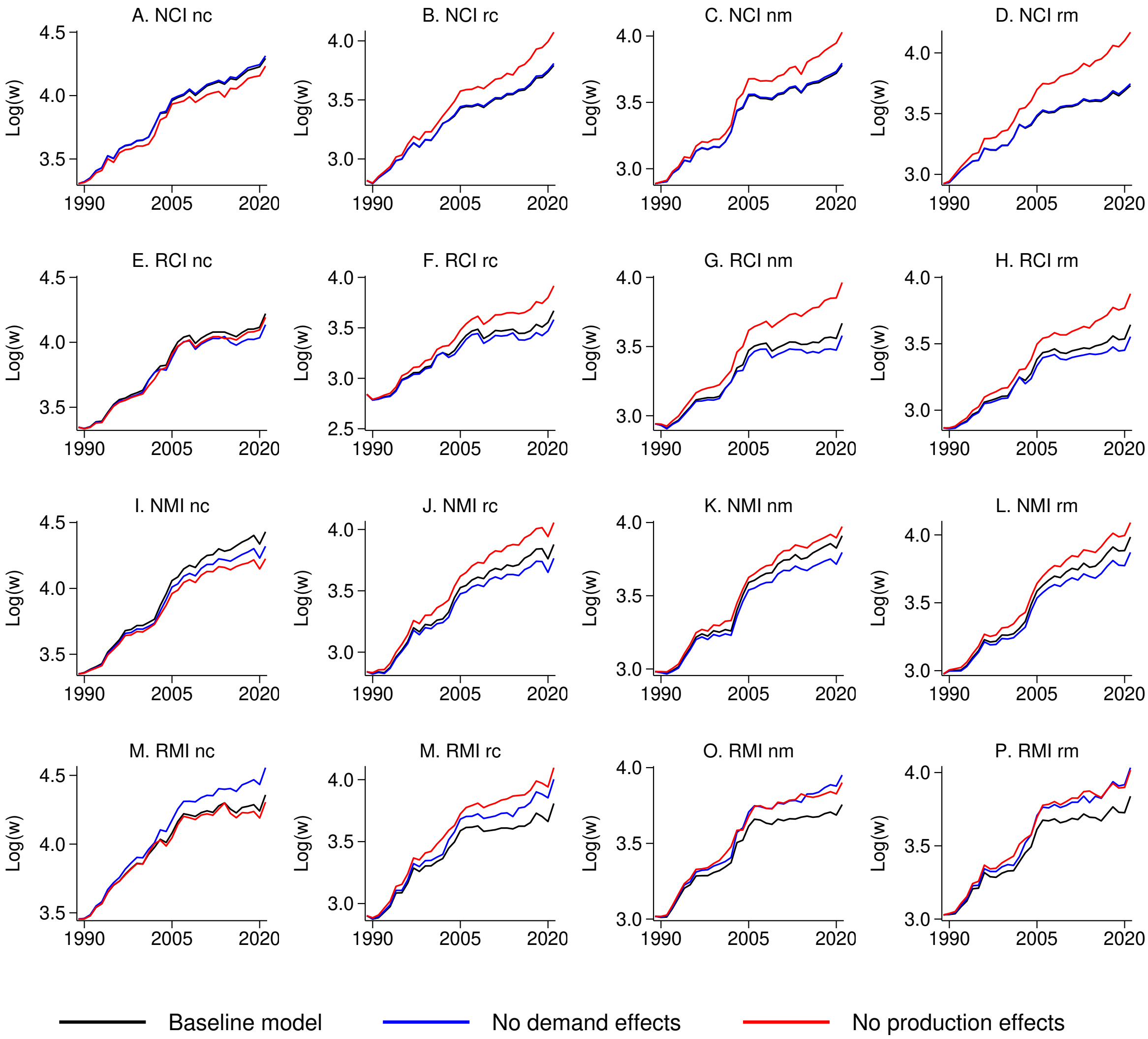

Figure A.27: Wage Counterfactuals Over Time for $\eta = 4.5$

Note: Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

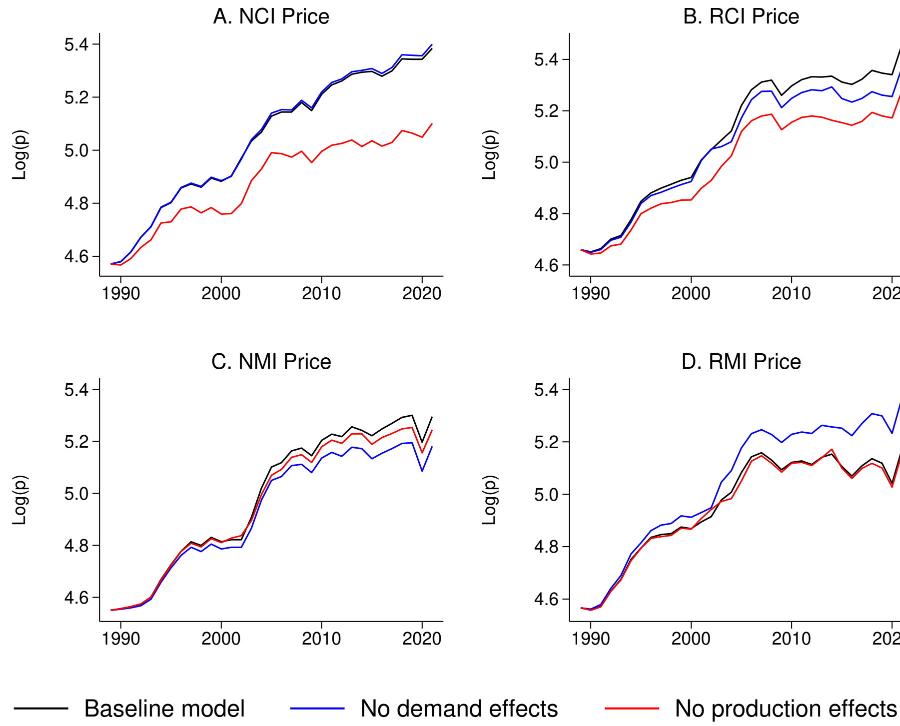

Figure A.28: Price Counterfactuals Over Time for $\eta = 4.5$

Note: Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

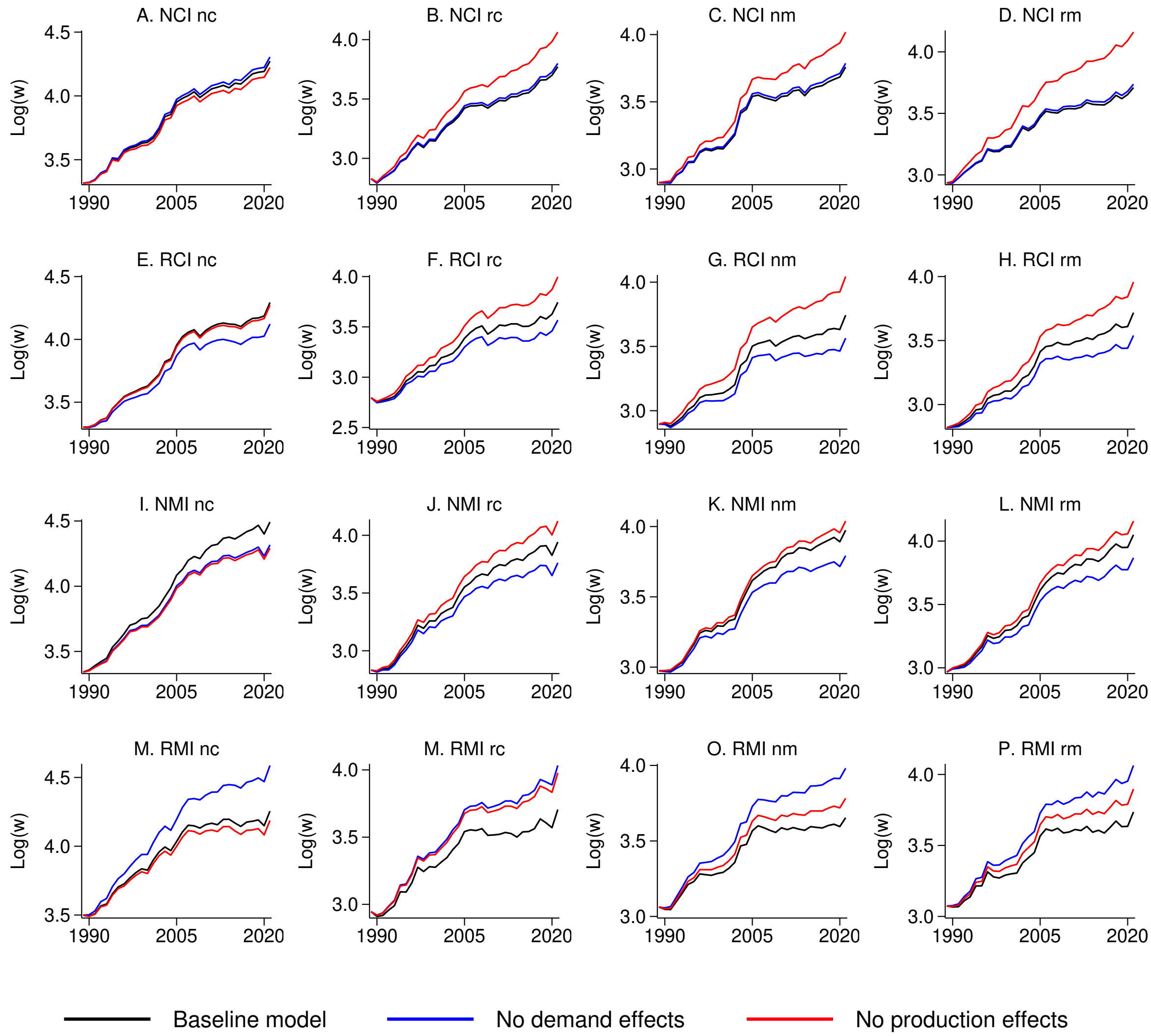

Figure A.29: Wage Counterfactuals Over Time With no Subsistence Levels

Note: Baseline model and counterfactuals with no subsistence levels solve for equilibrium allocations and prices when setting non-homothetic terms to 0. Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

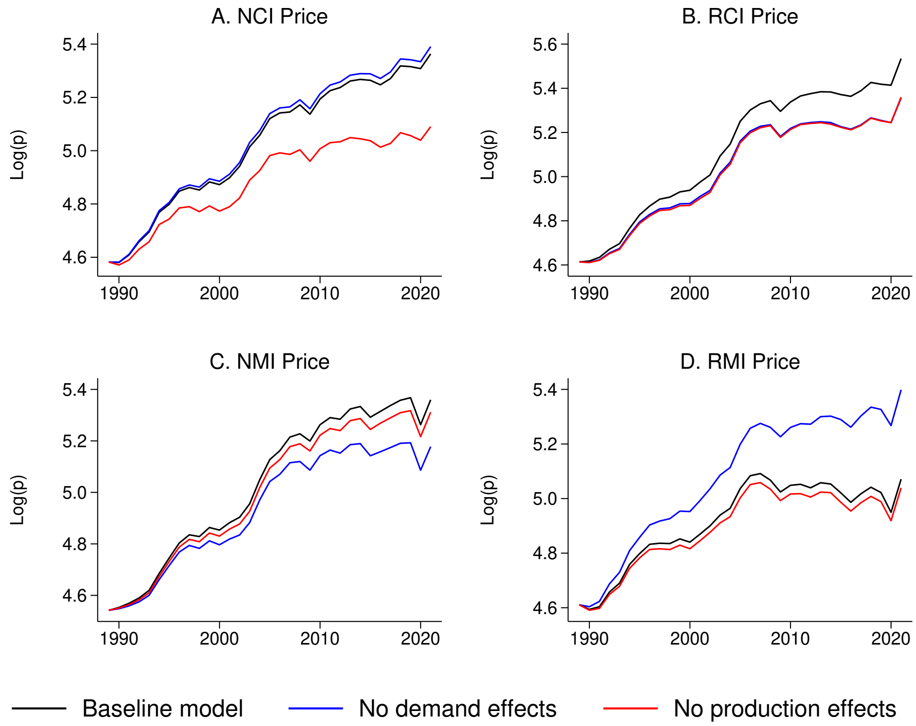

Figure A.30: Price Counterfactuals Over Time With no Subsistence Levels

Note: Baseline model and counterfactuals with no subsistence levels solve for equilibrium allocations and prices when setting non-homothetic terms to 0. Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

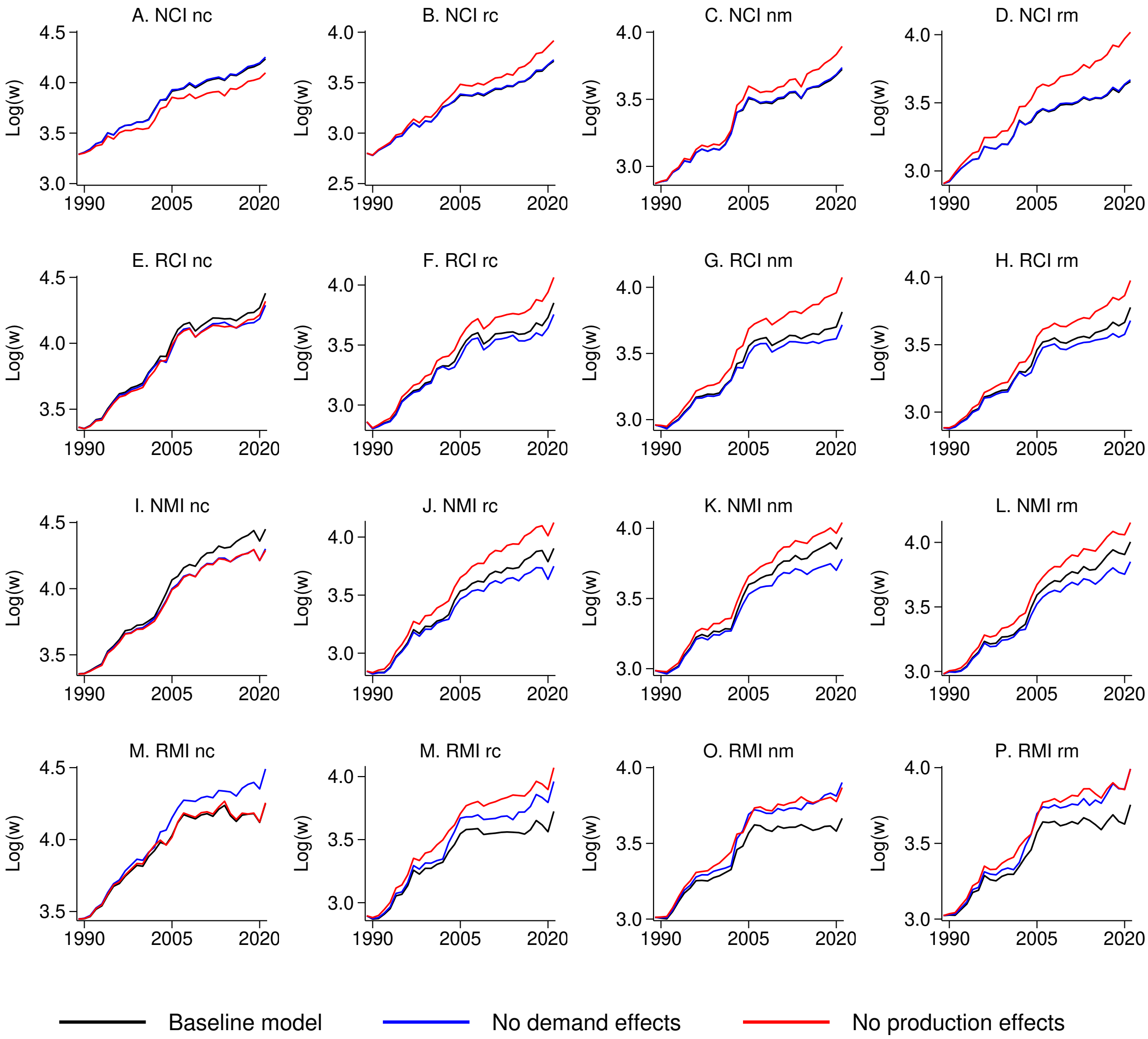

Figure A.31: Wage Counterfactuals Over Time with Adjusted labour Allocations Based on Output Quantities

Note: Labour allocations are adjusted at the sector level based on sector specific output. Wages are shown for 16 household-sector pairs, where nc is non-routine cognitive household, rc is routine cognitive household, nm is non-routine manual household, rm is routine manual household. NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

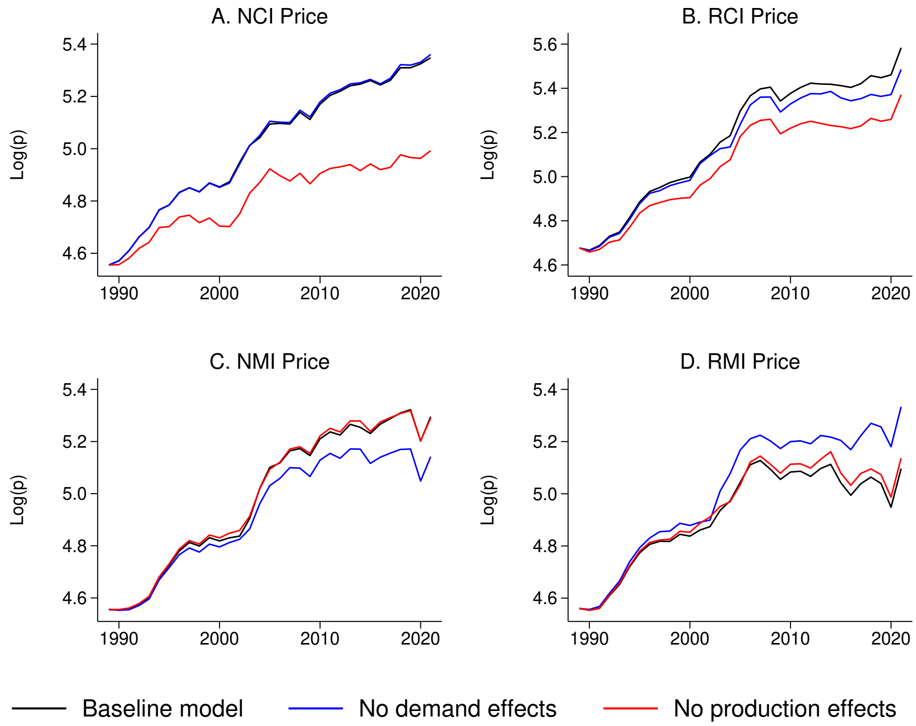

Figure A.32: Price Counterfactuals Over Time with Adjusted labour Allocations Based on Output Quantities

Note: Labour allocations are adjusted at the sector level based on sector specific output. Prices are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

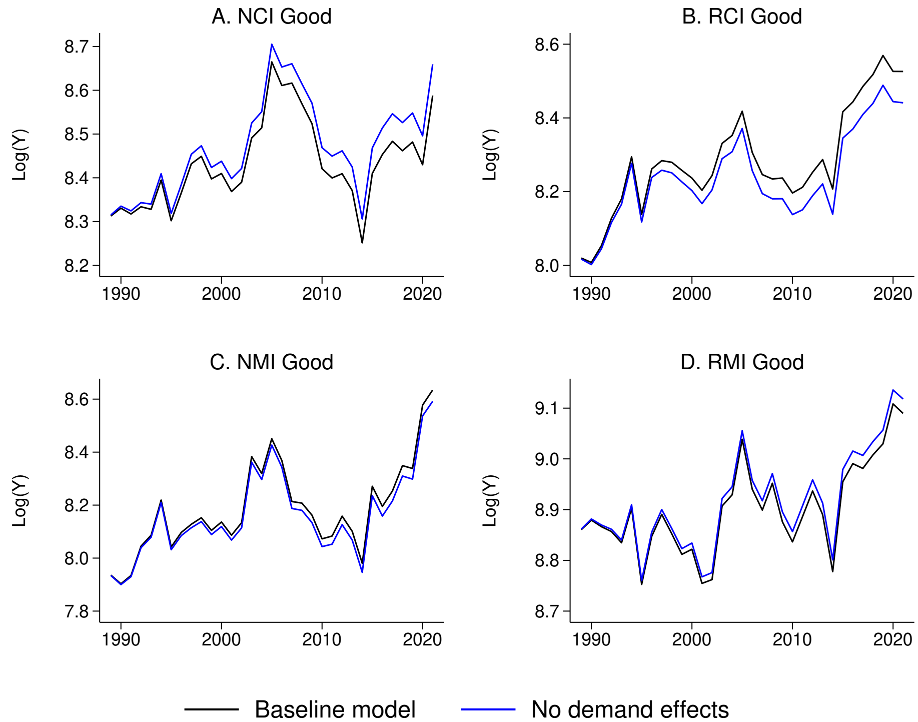

Figure A.33: Output Counterfactuals Over Time with Adjusted labour Allocations Based on Output Quantities

Note: Labour allocations are adjusted at the sector level based on sector specific output. Output quantities are illustrated for four sectors: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

Appendix B: Data

The analysis in this paper is based on a dataset that maps household level quarterly expenditure data to costs on capital and four types of labour – non-routine cognitive, routine cognitive, non-routine manual, and routine manual labour, that are employed in the production of the goods and services purchased by households. I construct the dataset through a series of mappings and aggregations, summarized in Figure B.1. The data sources include Consumer Expenditure Survey (CEX), National Income and Product Accounts (NIPA) Tables, Personal Consumption Expenditure (PCE) Bridge Tables, Input-Output Matrices, Integrated Industry-Level Production Account (KLEMS) data, Current Population Survey (CPS) data, and O*NET data.

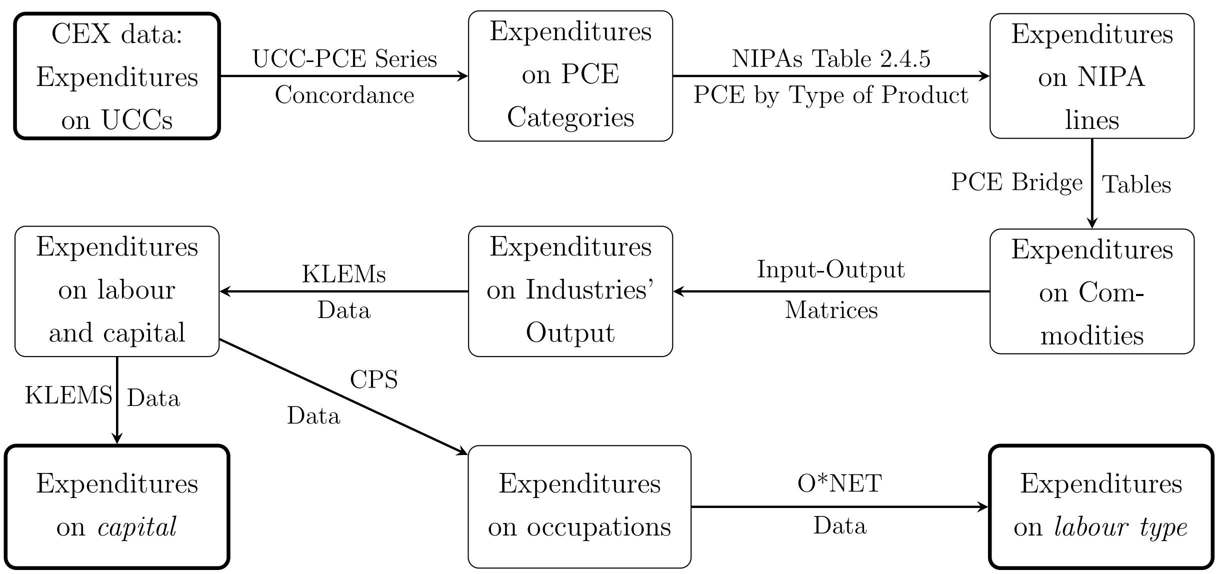

Figure B.1: Data preparation steps

Household-level expenditure data

Household expenditure data is taken from the Consumer Expenditure Survey (CEX). The CEX is a nationwide household survey conducted by the US Census Bureau for the Bureau of Labour Statistics (BLS) and is the only Federal household survey that provides information on the complete range of consumers' expenditures.[31] Specifically, I use the Interview Survey of the CEX. According to BLS, data from the Interview Survey on average annual expenditures together with global estimates for food and alcoholic beverages comprise about 95 percent of the total estimated spending, based on integrated Diary and Interview Survey data.[32] In the CEX, households are tracked for 5 consecutive quarters, and are interviewed for 4 quarters. After the fourth interview, the sample household is dropped and is replaced by a new household. In each quarter in the data, 25 percent of the consumption units are new units introduced into the sample to replace households that have completed their participation. Data collected in each quarter is treated independently, therefore the estimates do not depend on a particular household participating in the survey for all four quarters. I take data on household characteristics from FMLY family files, salary data from MEMB member files, and expenditure data from monthly expenditure MTBI files for the years 1989-2021.

I use SALARY variable from member files to get salary/wages for all household members. The variable reports: "During the past 12 months, what was the amount of wages or salary income received, before any deductions".[33] In 2004, BLS started providing an imputed income variable – SALARYX.[34] Using SALARYX for the years 2004-2021 instead of SALARY generates a shift in the income data compared to 1989-2004. To preserve consistency of the salary variable across all years in the data, I use variable SALARY for all years, except years 2004 and 2005 when the variable SALARY is not available. For the years 2004 and 2005, I use SALARYX variable instead.[35] I further adjust salaries and expenditures for household size, following Levinson and O'Brien (2019).

The sample is restricted to households with a reference person aged 25-65 with a non-missing occupation. I exclude top 1% and bottom 1% of households for each year based on household's total salary. Each household in the survey has a "replicate" weight that maps CEX households into the national population. Prior to aggregating expenditure data, I adjust the BLS provided weight based on the number of months in scope, following CEX representative population weights methodology[36].

[31] BLS CEX https://www.bls.gov/cex/

[32] CEX Handbook of Methods by BLS: https://www.bls.gov/opub/hom/cex/pdf/cex.pdf

[33] User's Guide to Income Imputation in the CE https://www.bls.gov/cex/csxguide.pdf

[34] CEX Improvements and protocol changes https://www.bls.gov/cex/ce-improvements.htm

[35] For this reason, I calculate the average expenditure share from income that I use in counterfactual analysis based on data for all, but 2004 and 2005 years, when unimputed salary variable is not available.

[36] CEX Getting Started Guide https://www.bls.gov/cex/pumd-getting-started-guide.htm

Table B.1: Summary Statistics by Household Type

Household type	Non-routine cognitive (1)	Routine cognitive (2)	Non-routine manual (3)	Routine manual (4)
Respondent's monthly salary	3,484.92	2,449.70	2,289.45	2,037.39
	(3,436.37)	(2,389.51)	(1,985.30)	(1,645.19)
Household's monthly salary	5,147.32	3,876.96	3,350.17	2,994.81
	(4,538.11)	(3,454.42)	(2,731.44)	(2,373.93)
Age	43.33	42.66	41.82	42.96
	(10.79)	(10.99)	(10.52)	(10.71)
Female=1	0.48	0.55	0.08	0.22
	(0.50)	(0.50)	(0.27)	(0.42)
Caucasian=1	0.82	0.82	0.90	0.81
	(0.39)	(0.38)	(0.31)	(0.39)
Married=1	0.59	0.54	0.69	0.62
	(0.49)	(0.50)	(0.46)	(0.49)
Less than high school	0.07	0.06	0.21	0.23
	(0.25)	(0.24)	(0.41)	(0.42)
High school	0.17	0.28	0.38	0.46
	(0.37)	(0.45)	(0.49)	(0.50)
Some college	0.18	0.28	0.22	0.19
	(0.38)	(0.45)	(0.41)	(0.40)
College degree	0.13	0.15	0.09	0.06
	(0.33)	(0.35)	(0.28)	(0.25)
More than college	0.46	0.22	0.10	0.05
	(0.50)	(0.42)	(0.30)	(0.22)
Urban=1	0.93	0.92	0.85	0.84
	(0.25)	(0.27)	(0.36)	(0.36)
N earners	1.78	1.76	1.85	1.83
	(0.78)	(0.78)	(0.84)	(0.85)
Household size	2.75	2.70	3.06	3.01
	(1.48)	(1.46)	(1.65)	(1.62)
N	369,148	170,814	61,998	83,292

Note: Standard deviations are in parentheses. Summary statistics are provided based on the answers of a respondent person. The sample is restricted to households with a reference person aged 25-65 with a non-missing occupation. I drop top 1% and bottom 1% of households for each year based on total household salary. Summary statistics are obtained using BLS provided weights, adjusted based on the number of months in scope. See Appendix B for more detail. Salaries are reported in nominal USD.

Table B.1 reports summary statistics by household type. Among the four household types, non-routine cognitive households have the highest salary. They also have the highest share of responders with higher education. In contrast, routine manual households have the lowest average salaries and the highest proportion of high school graduates (46%). The share of female responders varies substantially across household types, from 48% in non-routine cognitive to only 8% in non-routine manual households. Cognitive households are also more likely to live in urban areas compared to manual households.

Mapping expenditures to industries and occupations

The expenditures in the CEX data are categorized according to the Uniform Commercial Codes (UCCs) classification. The analysis sample contains 821 UCCs. These are detailed expenditures on goods and services purchased by households. For example, women's clothing expenditures are split into 16 UCCs, such as 380210 – Dresses, 380313 – Shirts, tops, and blouses, 380320 – Skirts and culottes, 380331 – Pants, 380332 – Shorts and shorts sets etc. I aggregate the UCC expenditures into 144 Personal Consumption Expenditures (PCE) categories – a component of the National Income and Product Accounts (NIPAs) produced by the Bureau of Economic Analysis (BEA) – using a CEX UCC- PCE Series concordance provided by the BLS.[37] For example, the 16 UCC codes detailing women's expenditures on clothing are aggregated into a PCE category titled "Women's and girls' clothing".

I then aggregate the PCE categories into 64 NIPAs lines expenditures using NIPAs Table 2.4.5 Personal Consumption Expenditures by Type of Product produced by the BEA.[38] Many of the PCE categories are the same as NIPAs lines. Women's and girls' clothing is an example of such a PCE category. Some of the PCE categories are aggregated into coarser NIPAs lines. For example, PCE categories Furniture; Window coverings; Carpets and other floor coverings; Clocks, lamps, lighting fixtures, and other household decorative items are aggregated into a Furniture and furnishings NIPAs line.

The NIPAs lines are then mapped to 53 commodity codes using PCE Bridge tables provided by the BEA.[39] These tables contain estimates of the commodity composition of the NIPAs lines and allow to calculate commodity shares for commodities comprising these NIPAs lines. For example, in addition to retail and transportation, Women's

[37] CEX UCCs to PCE Series Concordance https://www.bls.gov/cex/cepceconcordance.htm

[38] BEA NIPAs Table 2.4.5 Personal Consumption Expenditures by Type of Product https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2

[39] BEA PCE Bridge Tables https://www.bea.gov/industry/industry-underlying-estimates. At the time of data analysis, PCE Bridge Tables are available for years 1997-2018. The commodity composition of NIPA lines is fairly stable across years, thus the mapping between NIPA lines and commodities is established based on the average commodity composition of NIPA lines across the years in the PCE Bridge Tables.

and girls' clothing NIPAs line contains four commodities – Apparel, leather, and allied products, Textile mills and textile product mills, Miscellaneous manufacturing, Scrap, used, and secondhand goods. Furniture and furnishings NIPAs line contains 14 commodities, some of which are Wood products, Nonmetallic mineral products, Primary metals, Fabricated metal products, Plastics and rubber products etc. Some commodity codes were aggregated to match commodity codes from earlier Input-Output Tables. For example, commodity codes 481–Air transportation, 482–Rail transportation, 483–Water transportation, 484–Truck transportation, 485–Transit and ground passenger transportation, 486–Pipeline transportation, 487OS–Other transportation and support activities are aggregated to one Transportation commodity code. Mapping the NIPA lines to commodities is an important step as it converts purchaser's value and producer's value by adjusting for transportation and retail costs, which enables further mapping of the data to industry level data. Not adjusting for transportation and retail costs can lead to biased industry level estimates.

Next, I map households' expenditures on commodities to industries value added (VA) using yearly Input-Output (I-O) Tables produced by the BEA.[40] I use both Make/Supply and Use Tables. Make/Supply Tables show how much of each Commodity is produced by industries, whereas Use Tables show how much of each commodity is used by each industry in production. For example, the industries that contribute the most to the production of apparel, leather, and allied products – the largest commodity in the commodity structure of women's and girls' clothing, include apparel manufacturing, leather and allied products manufacturing, industries that manufacture textile and textile product mills, plastics and rubber products, as well as wholesale trade industry. Following this step, all final goods and services from the CEX data are mapped to 63 industries that produce these goods and service, with industry classification matching the one from the yearly Integrated Industry-Level Production Accounts (KLEMS) data.

Industries' VA is then allocated to labour and capital using KLEMS. KLEMS is produced by integrating BEA's GDP data by industry with capital and labour inputs data from the BLS, reporting capital and labour costs for each industry, as well as quantity indexes.[41] I calculate labour and capital shares of industries' VA from KLEMS data using industry capital and labour costs. This allows me to allocate VA from the previous step to labour and capital.

I then disaggregate industries' total labour costs to costs at the occupation level

[40] BEA Input-Output matrices: https://www.bea.gov/industry/input-output-accounts-data.

[41] KLEMs data https://www.bea.gov/data/special-topics/integrated-industry-level-production-account-

using Current Population Survey (CPS) data, provided by the BLS.[42] I use March outgoing rotation group (MORG) data, since it contains information on wages/salaries. Similarly to CEX sample restrictions, I focus on the sample with individuals aged 25-65 with non-missing occupations and industries. I also drop top 1% and bottom 1% of observations in each year based on salary. The sample covers over 420 occupations.

To split the total labour costs in an industry to occupations, I first aggregate salaries from CPS at the industry level using weights provided by the BLS. I then split the industry's wage bill based on the occupational wage bills within the industry. For example, occupations with the largest employment shares in the apparel manufacturing industry include production occupations, such as sewing machine operators, textile and garment pressers, textile cutting machine setters, operators, and tenders etc.

Following this mapping, all households' expenditures on UCCs in the CEX data are mapped to value added of labour at the occupation-industry level and capital at the industry level. For example, for a household that purchases a woman's dress, I know how much of the value of this dress is generated by labour employed in the occupations that produce this dress, and capital involved in the production of this dress. The final mapping includes aggregating occupation-level labour costs to non-routine cognitive, routine cognitive, non-routine manual, and routine manual labour.

Household and labour types

Autor et al. (2003) are the pioneers of a methodology that conceptualized a job as a series of tasks. They define a task as a unit of work activity that produces output. In their seminal paper, they focus on two main categories of tasks: routine tasks and non-routine tasks. Routine tasks have a repetitive nature and constitute a limited, well-defined set of cognitive and manual activities that can be easily codified. Non-routine tasks consist of activities that due to their nature and complexity cannot be carried out by computer executing programs.

Routine tasks are divided into routine cognitive tasks, such as bookkeeping and clerical work, and routine manual tasks, such as repetitive production on an assembly line. Similarly, non-routine tasks are divided into non-routine cognitive and non-routine manual tasks. Non-routine cognitive tasks consist of tasks that require abstract thinking, problem-solving, intuition, persuasion, and creativity. They can be further divided into analytical and interpersonal tasks. For example, task profiles of professional and

[42] BLS CPS ttps://www.bls.gov/cps/

technical occupations contain a high share of non-routine cognitive analytical tasks; and managerial occupations are commonly associated with a high share of non-routine cognitive interpersonal tasks. Non-routine manual tasks involve visual and language recognition, situational adaptability, and in-person interaction, which also precludes these tasks from being executed by programmed technologies. Examples of non-routine manual tasks include driving a truck through traffic or cleaning offices (Price and Price, 2013).

Occupations are split into the four labour types – non-routine cognitive, routine cognitive, non-routine manual, and routine manual labour, based on task intensity measures from O*NET. I follow Acemoglu and Autor (2011) in calculating task intensities of non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, non-routine manual, and routine manual tasks. The task intensity measures are based on data on ability, skill, and work context measures, listed in Table B.2.

The raw O*NET measures indicate importance of each individual task characteristic for an occupation on a scale from 1 to 5, with 1 being the least important, and 5 being the most important. To obtain task intensity measures for non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, non-routine manual, and routine manual tasks for each occupation, I first average the task measures for each occupation over all the years. I then add the O*NET measures for each one of these tasks and standardize these aggregated task measures for each occupation. This allows comparability of the task intensities across tasks for each occupation. The type of the occupation is determined by the largest task intensity. Occupations with the largest non-routine cognitive analytical or non-routine cognitive interpersonal measure belong to the non-routine cognitive type.

Table B.2: O*NET measures used for calculation of the task intensities

Task intensity measure	O*NET measures
Non-routine cognitive analytical task intensity	4.A.2.a.4 Analyzing data/information 4.A.2.b.2 Thinking creatively 4.A.4.a.1 Interpreting information for others
Non-routine cognitive interpersonal task intensity	4.A.4.a.4 Establishing and maintaining personal relationships 4.A.4.b.4 Guiding, directing and motivating subordinates 4.A.4.b.5 Coaching/developing others
Routine cognitive task intensity	4.C.3.b.7 Importance of repeating the same tasks 4.C.3.b.4 Importance of being exact or accurate 4.C.3.b.8 Structured v. Unstructured work (reverse)
Non-routine manual task intensity	4.A.3.a.4 Operating vehicles, mechanized devices, or equipment 4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls 1.A.2.a.2 Manual dexterity 1.A.1.f.1 Spatial orientation
Routine manual task intensity	4.C.3.d.3 Pace determined by speed of equipment 4.A.3.a.3 Controlling machines and processes 4.C.2.d.1.i Spend time making repetitive motions

Among the 420 occupations in the data, 139 occupations are of non-routine cognitive type. These occupations include a vast range of occupations, such as financial analysts, computer programmers, funeral directors, announcers, building inspectors, advertising sales agents, and bartenders. There are 82 routine cognitive occupations, such as credit analysts, stock clerks, mapping technicians, biological technicians, paralegals, and cashiers. Non-routine manual occupations include 107 occupations in the data, such as avionic technicians, photographers, coaches, paramedics, firefighters, janitors, and carpenters. Finally, 92 occupations are defined as routine manual. These include radiation therapists, dental hygienists, bakers, postal service mail sorters, and railroad conductors.

Figure B.2 contains average task intensity measures for the four tasks for 22 occupation groups. Non-routine cognitive task intensity is the larger of the non-routine cognitive analytical or interpersonal task intensities. All measures were rescaled to add to 1. Management and community/social services occupations have the largest relative cognitive task intensities, whereas installation, maintenance, and repair occupations have relatively high manual task intensities.

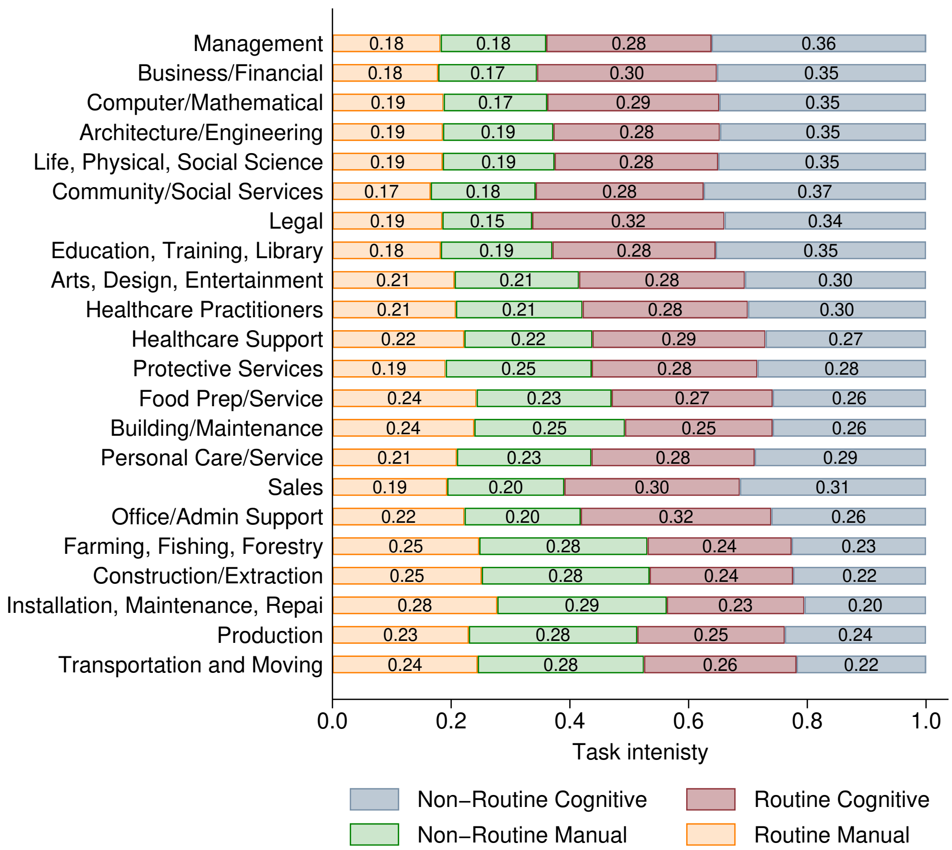

Figure B.2: Average Task Intensities by Occupation Group

Good and Sector types

Based on I-O Tables, final goods can be produced by multiple industries. To determine a good's type, I focus on the good's main industry – i.e. industry that produces the largest share of the good. I refer to this industry as the primary industry. For example, women's and girls' clothing is produced by apparel and leather and allied products industry, machinery industry, and farms industry among others. The apparel and leather and allied products industry has the largest VA share in the production of women's and girls' clothing compared to others, thus I define it to be the primary industry for women's and girls' clothing. The type of the good's primary industry determines good's type.

Using the definitions of the four labour types, I define an industry to be non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), non-routine manual intensive (NMI), or routine manual intensive (RMI) based on the relative occupational composition of industries. Specifically, I rank primary industries based on the labour share of the four occupation groups. I then select the top 25% of the industries with the largest value added share for each labour type. These industries with the relatively larger labour share of a specific type are assumed to be of the same type. For industries that had similar ranking for multiple task intensities, the type was determined based on the relatively larger labour share among the similarly ranked types. This industry definition captures relatively higher intensity of a particular labour type in an industry relative to other industries. Table B.3 lists primary industries by their type.

Good types are of the same type as the primary industry that produces these goods. Table B.4 lists NIPA lines by type. Figures B.3-B.6 show expenditures for the NIPA lines over time by type.

Table B.3: Primary Industries by Type

Non-routine cognitive intensive (NCI)	**Routine cognitive intensive (RCI)**
Computer and electronic products	Retail trade
Publishing industries, except internet	Broadcasting and telecommunications
Motion picture and sound recording industries	Insurance carriers and related activities
Data processing, internet publishing,	Legal services
and other information services	Administrative and support services
Federal Reserve banks, credit intermediation,	Ambulatory health care services
and related activities	Hospitals and nursing
Securities, commodity contracts, and investments	and residential care facilities
Real estate	Performing arts, spectator sports, museums,
Miscellaneous professional, scientific,	and related activities
and technical services	Accommodation
Educational services	Federal and State
Social assistance	Government
Food services and drinking places	
Non-routine manual intensive (NMI)	**Routine manual intensive (RMI)**
Farms	Oil and gas extraction
Forestry, fishing, and related activities	Food and beverage and tobacco products
Mining, except oil and gas	Textile mills and textile product mills
Utilities	Apparel and leather and allied products
Construction	Paper products
Wood products	Petroleum and coal products
Nonmetallic mineral products	Chemical products
Motor vehicles, bodies and trailers,	Plastics and rubber products
and parts	Primary metals
Warehousing and storage	Fabricated metal products
Other services, except government	Machinery
Transportation	Electrical equipment, appliances, and components
	Other transportation equipment
	Furniture and related products
	Miscellaneous manufacturing

Table B.4: NIPA Lines by Type

Non-routine cognitive intensive (NCI)	**Routine cognitive intensive (RCI)**
Household tools and equipment	Used motor vehicles
Video, audio, photographic, and information processing equipment and media	Group housing
Recreational books	Water supply and sanitation
Educational books	Physician services
Telephone and related communication equipment	Dental services
Magazines, newspapers, and stationery	Paramedical services
Other motor vehicle services	Hospitals
Recreational services	Nursing homes
Purchased meals and beverages	Ground transportation
Financial service charges, fees, and commissions	Membership clubs, sports centers, parks, theaters, and museums
Higher education	Audio, photo, video, and information processing services
Nursery, elementary, and secondary schools	Accommodations
Commercial and vocational schools	Life and health insurance
Social services and religious activities	House and motor insurance
	Telecommunication services
	Other services
Non-routine manual intensive (NMI)	**Routine manual intensive (RMI)**
New motor vehicles	Motor vehicle parts and accessories
Electricity	Furniture and furnishings
Natural gas	Household appliances
Motor vehicle maintenance and repair	Glassware, tableware, and household utensils
Air transportation	Sporting equipment, supplies, guns, and ammunition
Water transportation	Sports and recreational vehicles
Personal care and clothing services	Musical instruments
Household maintenance	Jewelry and watches
	Therapeutic appliances and equipment
	Luggage and similar personal items
	Food and beverages
	Women's and girls' clothing
	Men's and boys' clothing
	Children's and infants' clothing
	Other clothing materials and footwear
	Motor vehicle fuels, lubricants, and fluids
	Fuel oil and other fuels
	Pharmaceutical and other medical products
	Recreational items
	Household supplies
	Personal care products
	Tobacco

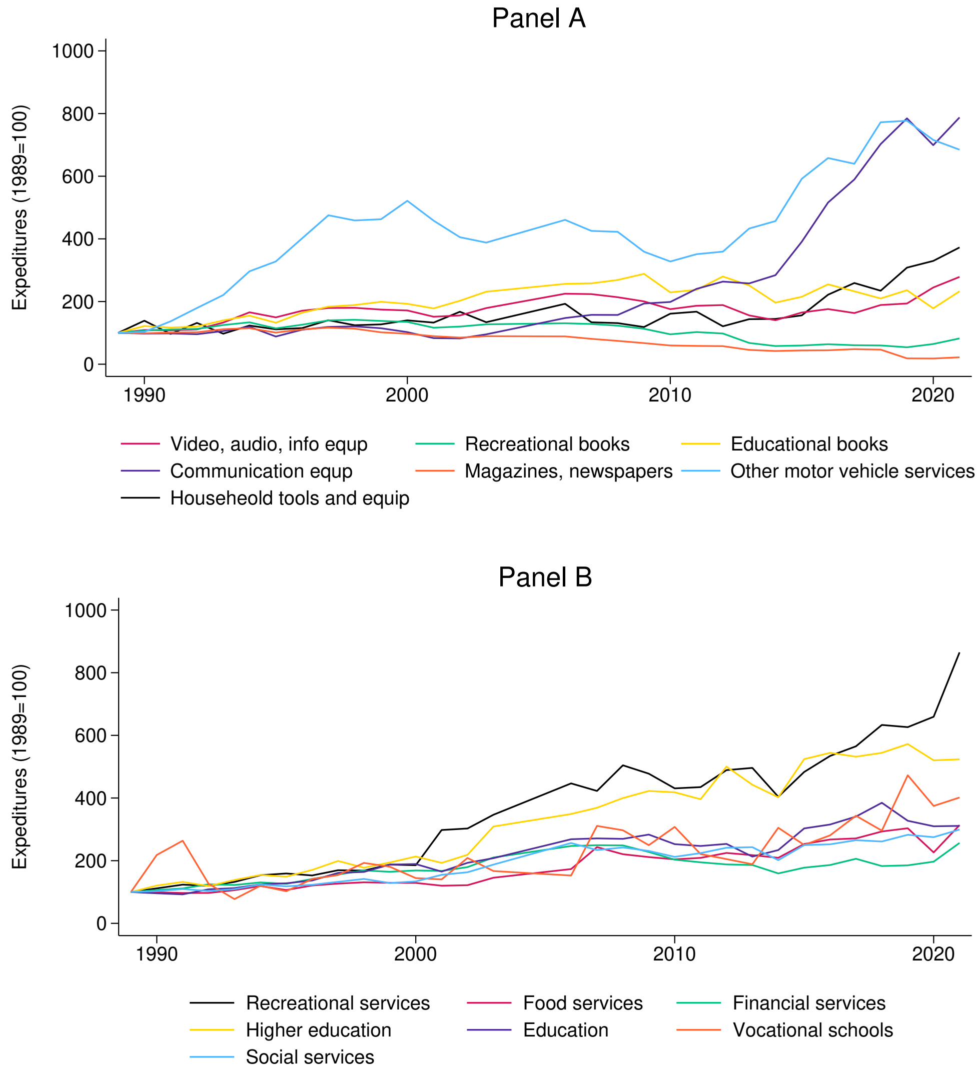

Figure B.3: Non-Routine Cognitive Intensive (NCI) NIPA lines

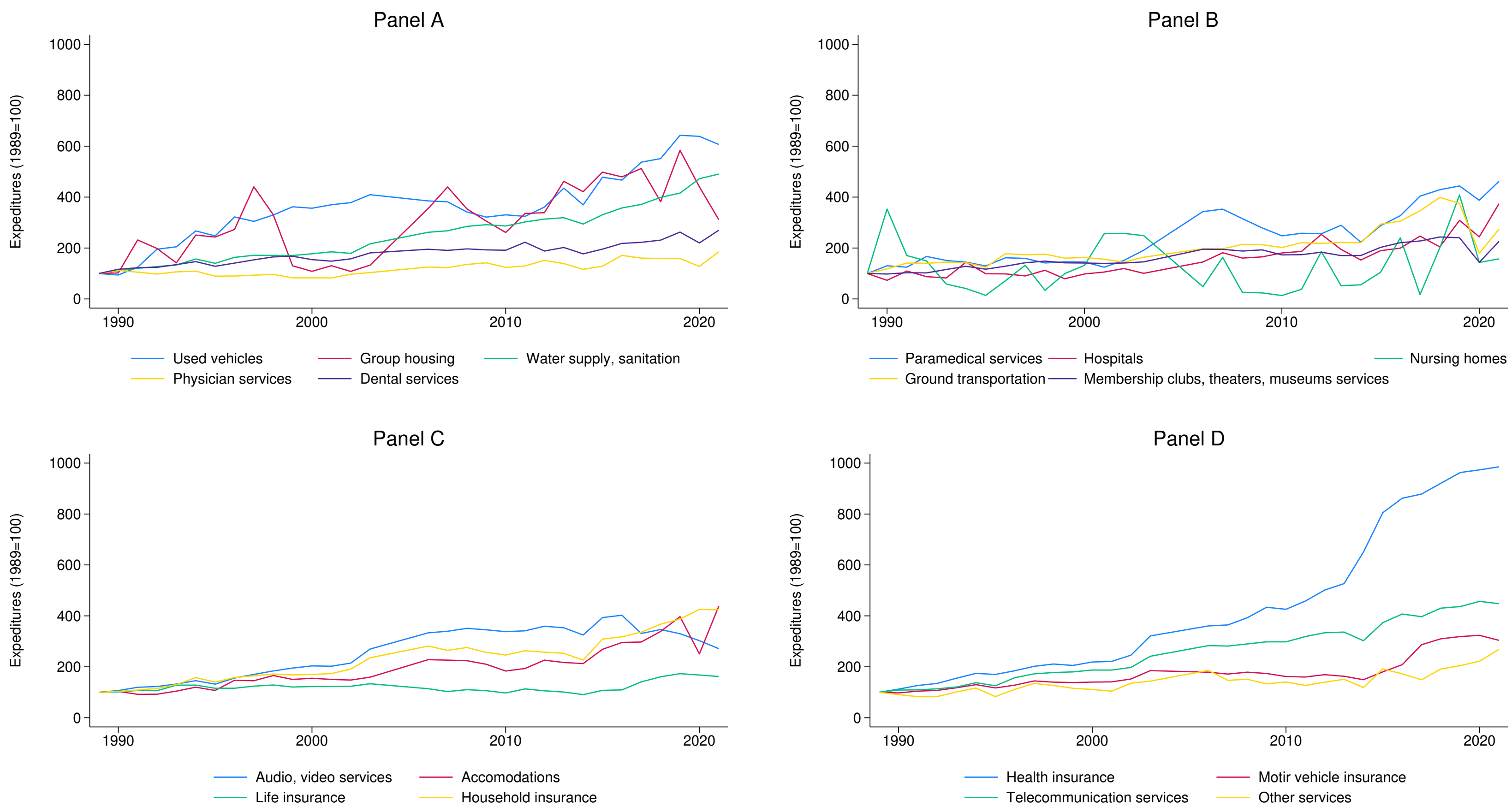

Figure B.4: Routine Cognitive Intensive (RCI) NIPA lines

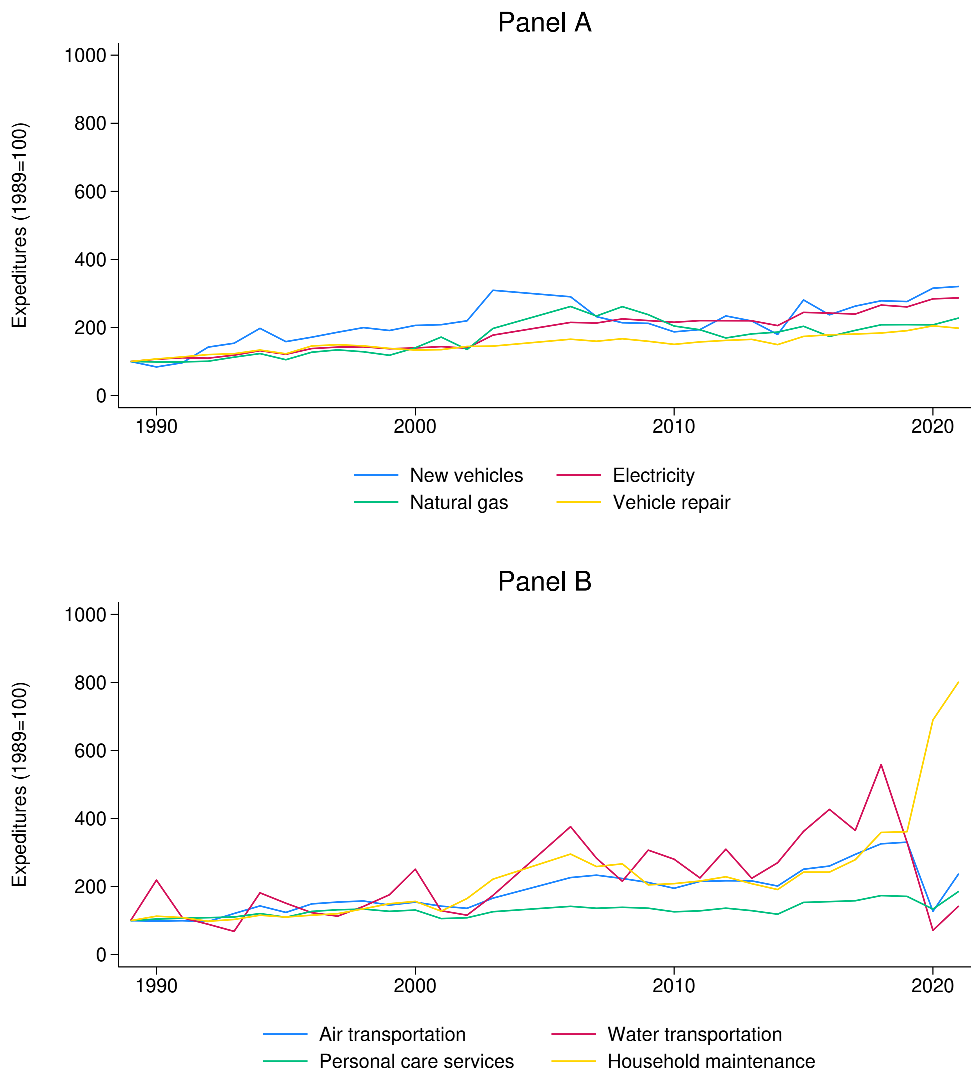

Figure B.5: Non-Routine Manual Intensive (NMI) NIPA lines

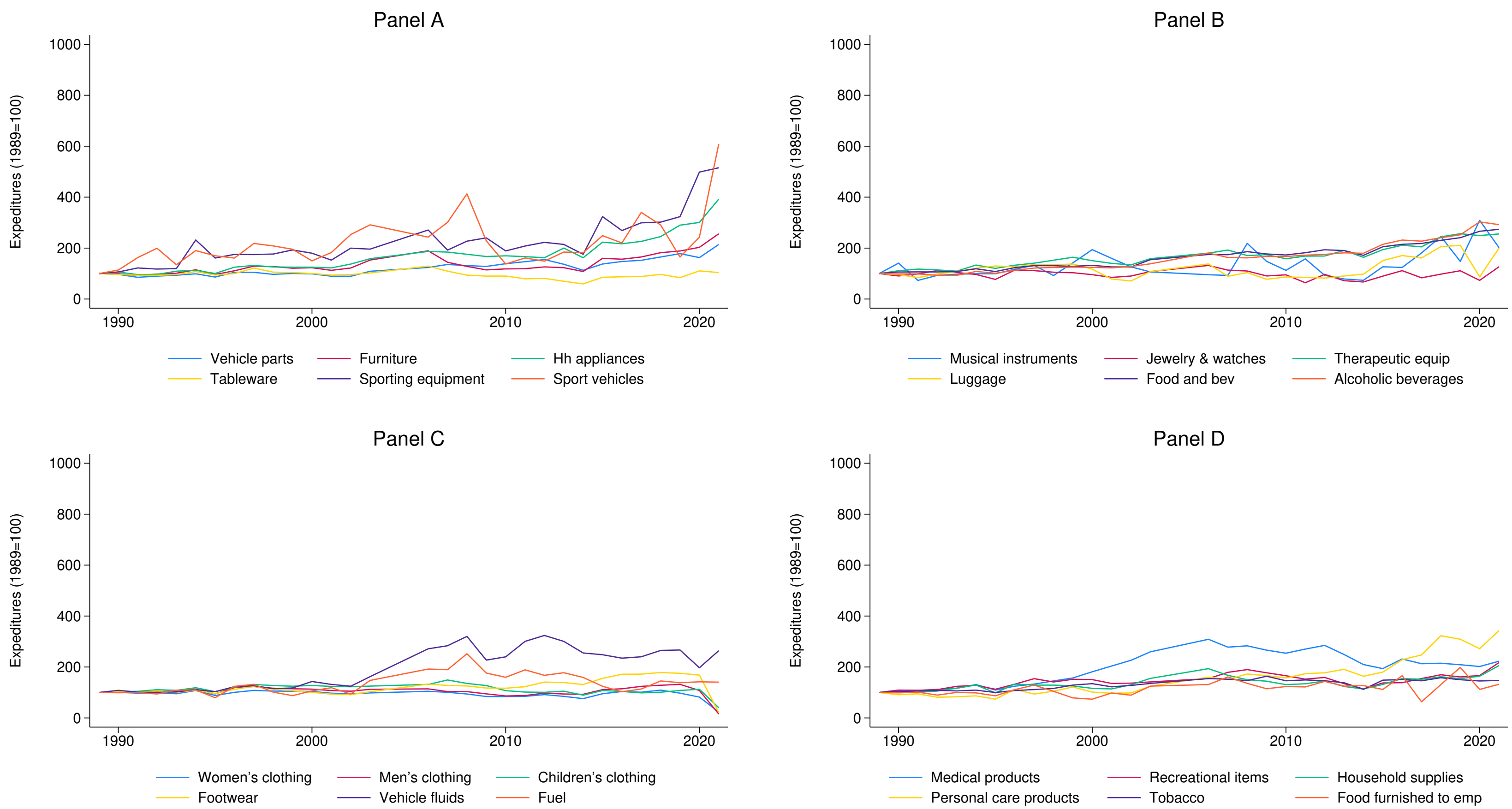

Figure B.6: Routine Manual Intensive (RMI) NIPA lines

Figure B.7 plots expenditures for the four goods, which are aggregated NIPA lines by type. Expenditures on the RCI good has increased the most over 1989-2021, followed by expenditures on NMI and NCI goods. Expenditure on the RMI good has increased the least. In 2021, expenditures on RCI and NMI goods have more than tripled compared to 1989. Changes in expenditures on the RCI good are driven by a sharp increase in expenditures on health insurance, as well as rising expenditures on telecommunication services, audio and video services, paramedical services, group housing, and sales of used vehicles. In 2021, households spend almost 10 times more on health insurance compared to 1989. Changes in expenditures on the NMI good come from increase in demand for transportation, as well as household maintenance, particularly in the recent years. In 2021, households spend almost 8 times more on household maintenance compared to 1989. Among the NIPA lines that comprise NCI good, expenditures on communication equipment, recreational services, higher education, and other motor vehicle services has increased the most. Expenditures on most NIPA lines within NMI good have remained fairly stable across time, with the exception of expenditures on sporting equipment and vehicles, vehicle fluids, and medical products.

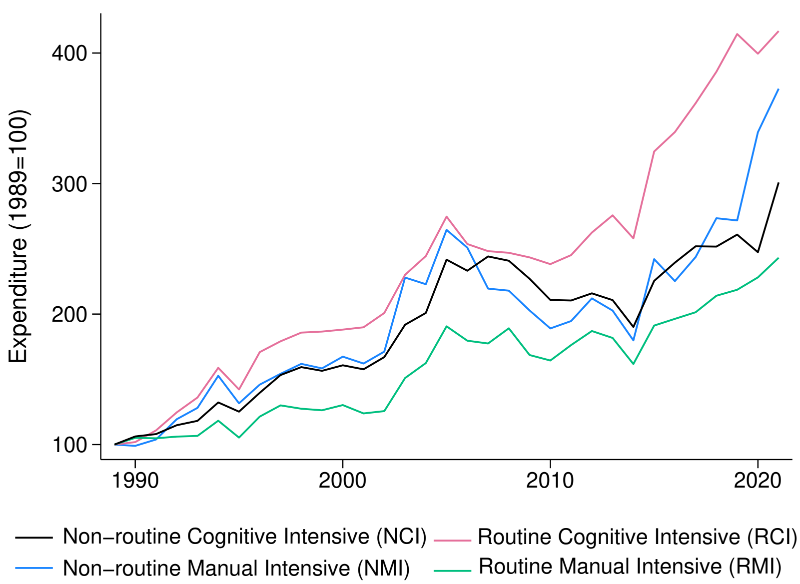

Figure B.7: Expenditures by Good Type Over Time

In the paper, rather than modelling multiple industries, I group all industries that produce a specific type of good into a sector of the same type. Thus, each good is produced by a sector of the same type. Industries that produce non-routine cognitive intensive goods are considered as a non-routine cognitive sector, while industries that produce routine cognitive intensive goods are considered as a routine cognitive sector. The same applies to non-routine manual and routine manual sectors.

The definition of sectors in this paper is different from the standard sector definitions in the structural transformation literature, where sectors are typically agriculture, manufacturing, and services. This difference is crucial when considering the variation in expenditures on different services. The services sector encompasses a wide variety of services, such as non-routine manual intensive landscape design and installation or non-routine cognitive intensive financial consulting services. The demand for these services can change differently over time. If the demand for these services is moving in different directions, grouping such services together would lead to a loss of important variation. This is especially important since many papers have documented a persistent reallocation of economic activity towards services (Herrendorf et al., 2013; Buera and Kaboski, 2012).

Table B.5 lists primary industries and their types from Table B.3 for agriculture, manufacturing, and services sectors. Both manufacturing and services sectors have multiple industry types comprising these sectors. The services sector is particularly heterogeneous. Out of the industries that comprise the services sector, 41% are non-routine cognitive intensive, 46% are routine cognitive intensive, and 13% are non-routine manual intensive. This highlights the importance of exploring dynamics in services at a more detailed level.

Table B.5: Industries and their Types in Agriculture, Manufacturing, and Services Sectors

Agriculture	**Manufacturing**	**Services**
Farms [NMI]	Computer and electronic products [NCI]	Publishing industries, except internet [NCI]
Forestry, fishing, and related activities [NMI]	Food and beverage and tobacco products [RMI]	Motion picture and sound recording industries [NCI]
	Textile mills and textile product mills [RMI]	Data processing, internet publishing, and other information services [NCI]
	Apparel and leather and allied products [RMI]	Broadcasting and telecommunications [RCI]
	Wood products [NMI]	Retail trade [RCI]
	Paper products [RMI]	Transportation [NMI]
	Printing and related support activities [RMI]	Warehousing and storage [NMI]
	Petroleum and coal products [RMI]	Federal Reserve banks, credit intermediation, and related activities [NCI]
	Chemical products [RMI]	Securities, commodity contracts, and investments [NCI]
	Plastics and rubber products [RMI]	Insurance carriers and related activities [RCI]
	Nonmetallic mineral products [NMI]	Real estate [NCI]
	Primary metals [RMI]	Rental and leasing services and lessors of intangible assets [RCI]
	Fabricated metal products [RMI]	Miscellaneous professional, scientific, and technical services [NCI]
	Machinery [RMI]	Legal services [RCI]
	Electrical equipment, appliances, and components [RMI]	Administrative and support services [RCI]
	Motor vehicles, bodies and trailers, and parts [NMI]	Educational services [NCI]
	Other transportation equipment [RMI]	Ambulatory health care services [RCI]
	Furniture and related products [RMI]	Hospitals and nursing and residential care facilities [RCI]
	Miscellaneous manufacturing [RMI]	Social assistance [NCI]
		Performing arts, spectator sports, museums, and related activities [RCI]
		Accommodation [RCI]
		Food services and drinking places [NCI]
		Other services, except government [NMI]
		Federal and State Government [RCI]

Note: NCI = Non-routine cognitive intensive, RCI = Routine cognitive intensive, NMI = Non-routine manual intensive, RMI = Routine manual intensive sector.

Since one good can be produced by multiple industries, as per I-O Tables, each industry can contribute to multiple sectors. For example, transportation and retail trade are among the industries that are involved in the production of goods in services in many sectors. However, each industry is strongly associated with one sector based on the type of the industry's main final product. Retail trade, while contributing to all sectors, has the largest contribution in the production of routine cognitive intensive goods relative to other goods, while transportation has the largest contribution in the production of non-routine manual goods. To match these sector definitions, production data is also grouped at the sector level, such that each sector produces VA, given by the total expenditures on the final goods produced by the sector, and labour and capital sector costs are the sum of the respective industry-level costs of industries that comprise the sector and contribute to the production of the sector's goods. Figure B.8 plots labour share for the four sectors over time.

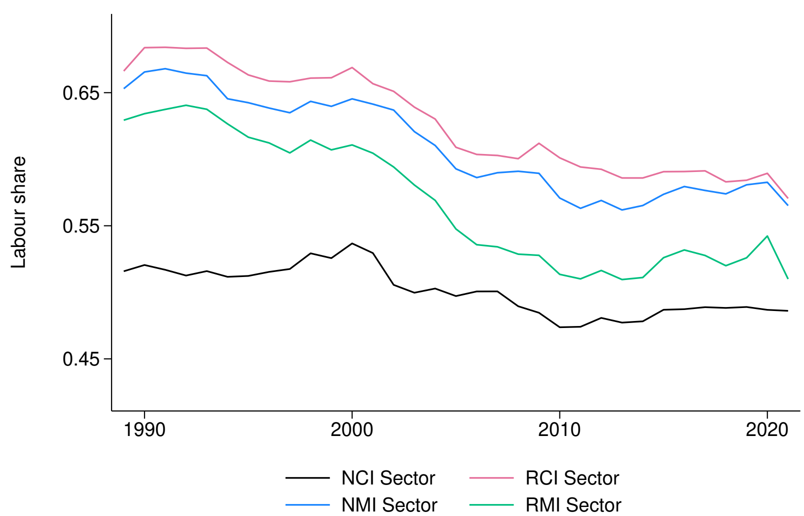

Figure B.8: Labour Share by Sector Over Time

Note: NCI is non-routine cognitive intensive sector, RCI is routine cognitive intensive sector, NMI is non-routine manual intensive sector, RMI is routine manual intensive sector.

The final step in preparation of the data is obtaining prices and quantities of the four types of final goods, purchased by households. To do this, I use yearly data on price indexes and total expenditures from the Personal Consumption Expenditure (PCE) Tables. Specifically, I use Table 2.4.4U. Price Indexes for Personal Consumption Expenditures by Type of Product and Table 2.4.5U. Personal Consumption Expenditures by Type of Product available through the BEA. [43] Table 2.4.4U. reports price indexes for the PCE categories. Table 2.4.5U. reports total expenditures for each PCE category. I calculate price of each of the four goods as a weighted average of price indexes of PCE categories that comprise the good type, using PCE expenditures as weights. While the expenditure data from the CEX is at the quarter-year level, all production data is at the annual level to match annual I-O Tables and KLEMS. Capital prices are based on capital quantity indexes from KLEMS, and labour type prices are salaries from CPS.

[43]NIPA BEA Table 2.4.4U. Price Indexes for Personal Consumption Expenditures by Type of Product https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=underlying. Table 2.4.5U. Personal Consumption Expenditures by Type of Product https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=underlying.

Appendix C: Monte Carlo Simulations

To assess the reliability of the estimation approach and validity of the identified parameters, I conduct Monte Carlo simulations calibrated to the characteristics of the empirical data. The simulation generates 5,000 synthetic datasets that replicate both the temporal and cross-sectional dimensions of the original data, comprising 132 quarterly observations over 1989-2021. Each synthetic dataset is constructed to preserve the data generating process implied by the theoretical model while incorporating stochastic elements.

The data generating process begins with price variables that follow trends similar to those observed in the actual data, with added random normal disturbances to capture market fluctuations. Total expenditure is generated with an upward trend and random variation to mirror observed spending patterns. Expenditure shares are then generated according to the non-homothetic CES with DGFs specification, using the estimated parameters from Section 5 as true values. Random normal disturbances are added to these shares to capture measurement error and preference shocks.

The estimation procedure incorporates several parametric constraints to ensure numerical stability and improve speed efficiency. The elasticity parameter η is parameterized to be greater than 1, reflecting both theoretical requirements and empirical evidence. The annual demand growth rates, λ's, are bounded between -1 and +1 using a hyperbolic tangent transformation. The estimation employs iterative feasible generalized non-linear least squares (IFGNLS), consistent with the approach used in the main analysis in Section 5.

The highly non-linear structure of the estimation equations, which involve multiplicative interactions between parameters and exponential terms, means that small perturbations in the data can occasionally produce extreme outliers through amplification of estimation error. To address this feature of non-linear systems, I examine results under different trimming thresholds for extreme values in the demand growth rate estimates. I construct two parameter samples. In the first sample, I drop top and bottom 2.5% of estimates for each of the demand growth rates, and in the second sample – top and bottom 5%.

Table C.1: Estimates from Monte-Carlo Simulations for the Non-Homothetic CES with DGFs Demand System

	CEX (1)	Monte Carlo (95%) (2)	Monte Carlo (90%) (3)
	Panel A: Elasticity		
η	2.700*** (0.502)	2.749*** (0.012)	2.758*** (0.013)
	Panel B: Utility weights		
ω_{NCI}	0.236*** (0.016)	0.244*** (0.001)	0.242*** (0.001)
ω_{RCI}	0.175*** (0.023)	0.181*** (0.001)	0.179*** (0.001)
ω_{NMI}	0.136*** (0.014)	0.111*** (0.001)	0.111*** (0.001)
ω_{RMI}	0.453*** (0.031)	0.464*** (0.001)	0.469*** (0.001)
	Panel C: Non-homotheticity terms/Subsistence levels		
$\bar{c}_{NCI}$	-767.284*** (69.410)	-766.202*** (2.342)	-760.228*** (2.018)
$\bar{c}_{RCI}$	-647.045*** (54.289)	-647.219*** (1.878)	-642.821*** (1.596)
$\bar{c}_{NMI}$	-505.372*** (58.994)	-529.374*** (3.021)	-517.386*** (2.083)
$\bar{c}_{RMI}$	-1,238.245*** (85.202)	-1,254.409*** (4.280)	-1,238.514*** (3.531)
	Panel D: Annual demand growth rates		
λ_{NCI}	0.092*** (0.005)	0.018*** (0.001)	0.018** (0.001)
λ_{RCI}	0.110*** (0.007)	0.038*** (0.001)	0.038*** (0.001)
λ_{NMI}	0.112*** (0.009)	0.047*** (0.001)	0.047*** (0.001)
λ_{RMI}	0.063*** (0.007)	-0.025*** (0.001)	-0.011*** (0.001)
	Panel E: Differences in the demand growth rates		
$\lambda_{RCI} - \lambda_{NCI}$	0.018*** (0.005)	0.022*** (0.001)	0.020*** (0.001)
$\lambda_{NMI} - \lambda_{NCI}$	0.019*** (0.007)	0.036*** (0.002)	0.029*** (0.001)
$\lambda_{RMI} - \lambda_{NCI}$	-0.029*** (0.007)	-0.030*** (0.001)	-0.029*** (0.001)

Note: Column (1) reproduces estimates from the quarter-year aggregate CEX data over the period 1989-2021 from Table 2 (N=132). Columns (2) and (3) present results from Monte Carlo simulations with different sample sizes based on trimming of outliers. Column(2) drops top and bottom 2.5% for each of the four demand growth rates (N=3,498), and column (3) drops top and bottom 5% for each demand growth rate (N=2,994). Estimates are obtained from a demand system consisting of FOCs for three expenditure shares – non-routine cognitive intensive, routine cognitive intensive, and routine manual intensive good shares. Equation for expenditure share of routine manual intensive good was dropped to avoid a singular error covariance matrix. Standard errors are in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

The simulation results, presented in Table C.1, demonstrate strong consistency between the estimated and true parameter values for most model parameters. Column (1) reproduces estimates from Section 5, while columns (2) and (3) report estimates from the Monte-Carlo simulations for the samples under two outlier trimming thresholds. The elasticity parameter, η, and subsistence levels are particularly well-estimated, with narrow confidence intervals containing the true values.

While the point estimates of individual demand growth rates, λ's exhibit some sampling variability, their pairwise differences, which give rise to structural change in the model, are estimated with high precision. Panel E in Table C.1 demonstrates that the estimated differences in demand growth rates exhibit remarkable stability across simulations and correspond closely with the point estimates obtained using CEX data. The estimated growth rate differences are within the 99% confidence intervals for each other in all three columns, providing strong evidence for the identification of these differences.

Figure C.1 presents the sampling distributions of the estimated differences in demand growth rates after trimming top and bottom 2.5% for each of the four demand growth rates. The distributions exhibit well-behaved approximately normal shapes centered near the empirical point estimates, with relatively small standard errors, showing great precision in estimation of differences in the demand growth rates.

The Monte Carlo evidence thus provides strong support for the identification and consistent estimation of the model's structural parameters, particularly the critical differences in demand growth rates across sectors. While individual parameter estimates exhibit expected sampling variation, the differences that identify the model's core implications for structural change and inequality are precisely estimated and robust. This parameter stability is essential given their central role in the paper's conclusions regarding the evolution of consumer demand and its distributional implications.

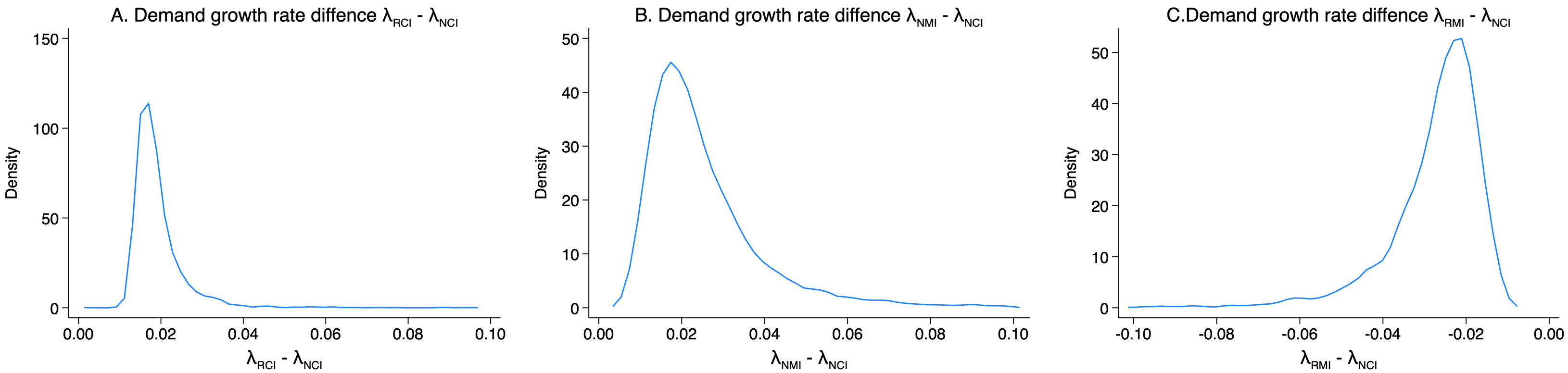

Figure C.1: Distribution of Differences in Demand Growth Rates from Monte-Carlo Simulations

Note: Differences in the demand growth rates are shown after dropping top and bottom 2.5% for each of the four demand growth rates from the Monte-Carlo simulations (N=3,498). λ_{NCI} is the annual demand growth rate for non-routine cognitive intensive good, λ_{RCI} is the annual demand growth rate for routine cognitive intensive good, λ_{NMI} is the annual demand growth rate for non-routine manual intensive good, and λ_{RMI} is the annual demand growth rate for routine manual intensive good. Each difference in the demand growth rates was binned up. Values of λ_{RCI}-λ_{NCI} and λ_{NMI}-λ_{NCI} were replaces with -0.001 if the value of the differences were below - 0.001, and 0.1 if values of the differences were above 0.1. Values of λ_{RMI}-λ_{NCI} were replaced with -0.1 if values of the difference were below -0.1, and 0.001, if values of the difference were above 0.001.