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

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Job Market Paper

October, 2024

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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, 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 how consumers spend their money (Saez and Zucman, 2020; Piketty et al., 2018). In the US, health insurance expenditures are now ten times higher than in the 1990s, household maintenance spending has increased eight-fold, and demand for various services has surged. While extensive research has demonstrated how technological change drives inequality by disproportionately benefiting skilled and non-routine workers (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022), the effect of changing consumer demand on the income distribution remains largely unexplored. Shifts in consumption patterns directly affect demand for workers producing different goods and services – as consumer spending reallocates 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 of 1989-2021 and show that these changes are heterogeneous across different households and goods. Third, I demonstrate a substantial impact of DGFs-driven demand effects on wages and income inequality, with demand changes often counteracting the negative effects of technological change. In the absence of changes in demand, the rise in income inequality, captured by the coefficient of variation (CV), would have been 73% larger. Changes in demand have 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, thereby widening wage differentials (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 given less attention to how evolving consumer demand might 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, uses 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 shifters, 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 type of 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 endogenous 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

[1]I split households into four types – non-routine cognitive, routine cognitive, non-routine manual, and routine manual, based on 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.

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 Accounts (KLEMS), Current Population Survey (CPS), and the Occupational Information Network (O*NET) data. Expenditure data is aggregated at the level of four households, and labour employed by sectors is split at the level of four occupation groups that are of the same four types as households. 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. Strikingly, the magnitude of changes in income inequality due to demand effects is over 94% of that of production effects, but in the opposite direction. This finding suggests 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. These results complement much of the existing literature that focuses primarily on technological change as the driver of inequality (e.g., Acemoglu and Restrepo (2022)), highlighting the critical importance of demand-side factors.

I find that up to 20% of the DGF-driven demand effects arise from changes in household

[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.

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 demand effects that counteract negative production effects on income inequality. 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 demonstrating how evolving demand patterns interact with changing skill composition to affect inequality.

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 on labour and capital employed in 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). In addition, 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 labour 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 into four types based on tasks – non-routine cognitive, routine cognitive, non-routine manual, and routine manual. Following Acemoglu and Autor (2011), I construct occupation-specific task intensity measures using O*NET data. The type of the occupation is determined by the largest task intensity. The data covers 420 occupations, and each labour type includes a vast variety of occupations by skill and education level. Out of the 420 occupations, 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. Routine cognitive type includes 82 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.

I use this definition of labour types to categorize industries as non-routine cognitive intensive (NCI), routine cognitive intensive (RCI), non-routine manual intensive (NMI),

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

and routine manual intensive (RMI). Industries are classified based on their relative occupational composition – 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 relatively higher intensities of the use of a particular labour type in production relative to other industries. Good types are determined by the type of industry that produces this 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 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 typically divide the economy into agriculture, manufacturing, and services sectors, whereas this paper defines sectors based on the nature of work, captured by task intensities. This approach 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, or routine cognitive intensive insurance services. 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.[7] The demand for different services can change differently over time. If these trends in demand are moving in different directions, grouping all services together would lead to a loss of important variation. 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). Treating services as a homogeneous sector may mask important dynamics in structural transformation.

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

[5]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. For more detail, see Appendix B. Table B.3 lists main industries by their type.

[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. 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 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. The type of the good's primary industry determines good's type. 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.

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 labour type wages are given by salaries from the MORG CPS.

The sample 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 expenditures on the four goods by household type for each quarter using weights provided by the BLS that map CEX households into the national population.[9,10] The resulting dataset contains expenditures for the four aggregate households – non-routine cognitive, routine cognitive, non-routine manual, and routine manual, over the period from 1989 to 2021. 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. I use this dataset for all analyses in the paper.

Figure 1 documents substantial heterogeneity in the evolution of expenditure shares and price dynamics across goods over the period 1989-2021.[11] The expenditure shares of the RCI good increased the most over 1989-2021, followed by the expenditure share of NMI good. Price of 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 NCI good remained fairly stable over time. In 2021, expenditures on 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 expendi-

[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.

[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 salary and expenditures, following Levinson and O'Brien (2019). Adjusting or not adjusting salaries or expenditures for household size does not meaningfully affect the results in the paper.

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

tures 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 increase in expenditures on transportation, as well as household maintenance, particularly in the recent years. 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 across time, with the exception of expenditures on sporting equipment and vehicles, vehicle fluids, and medical products.[12] Such heterogeneity in consumption patterns across 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 possibility of changing consumer demand over time, potentially 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 relevance 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 consumption patterns 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): $CV = \frac{SD_{Income}}{Average\ Income}$

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 consumption structure arise through a novel channel – demand shifters, given by endogenous 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. 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 preference specification is given by 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, such as in the case of smartphones or social media platforms. These effects are not adequately captured by traditional models. 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. As shown in Goolsbee and Klenow (2006), products like the internet exhibit rising utility with increased usage, and 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 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. Households supply labour, denoted by household type i, to all four sectors, and 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 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, as shown in equation 1.

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

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

Here, 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 $\bar{c}_{ij}$ 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 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 household's expenditure on the four goods in the budget constraint to equal household's total expenditure in a given period, denoted

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

$$\varepsilon_{ijm} = \eta \frac{d\, log\left(\frac{c_{ijt}+\bar{c}_{ij}}{c_{imt}+\bar{c}_{im}}\right)}{d\, log\left(\frac{c_{ijt}}{c_{imt}}\right)}$$

[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.

by C_{jt}.[17] 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 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 nominator and numerator 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

[17] In counterfactual analysis, I express household's total expenditure as a share of income. Section 4.3 discusses this step in more detail.

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 : four types of labour – nc, rc, nm, and rm – and sector-specific capital. The cost minimization problem[18] 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 endogenous 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., 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). 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.[19] This specification is particularly relevant in the production structure

[18] 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.

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

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:

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

Here, α's 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 σ's. The elasticity of substitution between factor pairs is given by the Allen-Uzawa elasticity (AES), introduced by Allen (1938) and extended by Uzawa (1962).[20] 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 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.

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

[20] 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).

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 endogenous 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 optimal 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 endogenous 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 of interest govern household's and firms decision-making include utility function weights, ω's, annual demand growth rates, λ's, non-homotheticity terms, $\bar{c}$'s, and elasticity parameter, η from the household's problem, and annual factor augmenting technical growth rates, γ's, and CRESH elasticity parameters, σ's from the sector's problem. I estimate these parameters separately from the household's and sector's problems using quarterly data as 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. This section discusses estimation approach to recover the parameters of interest in this model, as well as the identifying variation the estimation is based on. I then present the counterfactual analysis approach, which allows to explore the importance of changing demand on income distribution and income inequality.

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's 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 total consumption of a household provides an expression for the consumption shares of goods:

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

Expressing the demand system using good shares allows to simplify the system of equations to 12 in place of the original 16. This is because now the dependent variables in this system of equations are expenditure shares, which sum to one for each household. Including all 16 share equations will result in a singular covariance matrix. To avoid this issue, I drop the estimation equation for routine manual goods for each household.[21]

In the model, utility weights of 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:

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

[21]The estimation results do not depend on equations for what good are dropped.

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

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 comprises 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 demand shifters 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 over longer period of time allows to abstract from short-term fluctuations that might be driving the differences in the annual demand growth rates. 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, which result in changes in expenditure structure, as shown by equation 4, across CEX and NIPA expenditures will reinforce reliability of the estimates for further counterfactual analysis.

The identification of parameters of interest relies on distinct sources of variation in the data. The elasticity parameter, η, is identified from changes in relative prices and corresponding shifts in expenditure shares over time for all goods. The good-specific non-homotheticity parameters, $\bar{c}$'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 price and income variations. 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 income or prices – residual time-dependent variation in the standard non-homothetic CES demand system. The key identifying assumption to obtain estimates of λ's is presence of systematic time trends in consumption patterns after accounting for price and income effects. Non-linearity of the system of equations is another attribute that aids identification, as discussed in more detail in (León-Ledesma et al., 2010).

Estimating the demand system at the household level introduces additional challenges. Estimating the model at the aggregate level reduces dimensionality of the problem, and aggregate economy level data behaves more smoothly compared to household-level aggregate data, since aggregating expenditures across households smooths out idiosyncratic household-level variation. In a system of 12 non-linear equations, this makes it difficult to isolate η and ω's – parameters that are common across households. For this reason, 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, as described above. Constraining η and ω's to be the same across households reduces the computation burden while maintaining flexibility in modelling household-level consumption behaviour. Importantly, even when η and ω's are the same across household types, estimates of household-specific non-homotheticity terms, $\bar{c}$'s, will adjust to capture the household and good-pair specific elasticities of substitution, while 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, not accounted for by equalizing ω's across households. As equation 4 shows, it is the differences in the good-specific λ's, rather than their absolute values, that drive household's relative consumption choices and, thus, structural change in consumption. Thus, in the household-level demand system, the changes in the consumption structure that arise through DGFs are well identified.

4.2 Sector's Problem Estimation

The solution to a sector's problem with production function given by equation 6 consists of five FOCs – one for each factor hired by the sector: four types of labour, as described above, and capital. First-order conditions (FOCs) for labour type i and capital, hired by sector j is given by equations 8 and 9. With four sectors producing four final goods, sectors' solutions, together with their respective production functions, give rise to a system of 24 equations that determine production structure and sector's choices in equilibrium. Similar to the household's problem, I consider these equations jointly. Performing estimation for all four sectors together allows for the error terms to be correlated across sectors. I normalize these equations prior to estimation, following León-Ledesma et al. (2010) and Herrendorf et al. (2015).

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 the production inputs being measured in different units. Without including the non-linear production function as part of the estimation system, normalization points in the linear FOCs may be absorbed by constants, leading to biased estimates. Estimating the FOCs alongside the production function ensures that cross-equation parameter constraints are met, facilitating joint identification of the technical growth rates.

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. 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 (Herrendorf et al., 2015). For this reason, I normalize the production function using geometric averages for good output, four types pf labour, and capital, denoted by $\overline{Y}_{ij}$, $\overline{L}_{ij}$, and $\overline{K}_j$. The arithmetic average of time is given by $\bar{t}$.

Applying the logarithmic transformation to the normalized production function and FOCs for labour and capital gives:

$$\log(Y_{jt}) = \log(\overline{Y}_j) + \frac{\sigma_j}{\sigma_j - 1} \log \Bigg[\frac{\sigma_j - 1}{\sigma_j} \frac{\sigma_{Kj}}{\sigma_{Kj} - 1}\, \overline{\theta}_{Kj} \left(e^{\gamma_{jk}(t-\bar{t})} \frac{K_{jt}}{\overline{K}_j} \right)^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} + \sum_{\substack{i=nc,\, rc,\\ nm,\, rm}} \frac{\sigma_j - 1}{\sigma_j} \frac{\sigma_{Lij}}{\sigma_{Lij} - 1}\, \overline{\theta}_{Lij} \left(e^{\gamma_{Lij}(t-\bar{t})} \frac{L_{ijt}}{\overline{L}_{ij}} \right)^{\frac{\sigma_{Lij}-1}{\sigma_{Lij}}} \Bigg] \tag{13}$$

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

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

Equations 13-15 describe the final 6 normalized equations for each sector – production function (equation 13), normalized FOC for labour types $i \in \{nc, rc, nm, rm\}$ (equation 14), and FOC for capital (equation 15). 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.[22] Adding an error term, representing productivity shifters

[22]In the case of CES production function, with normalization the exponents equal income shares, 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:

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

or measurement error, to all 6 equations for each of the four sectors gives the final system of 24 equations that I estimate jointly using non-linear 3SLS. Following Herrendorf et al. (2015), I use lagged variables for endogenous right-hand side variables as instruments.[23]

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 responsiveness of factor prices to changes in aggregate output and factor inputs over time. The identifying variation for technical growth rates, γ_{Lij}'s and γ_{Kj}'s, comes from trends in factor prices that cannot be explained by changes in aggregate output and factor inputs. Presence of time-dependent changes in wages and capital rent that are independent from their changes due to differences in output and inputs is a key identifying assumption for estimating factor augmenting technical growth rates. Including the production function alongside the FOCs enforces the cross-equation restrictions, which ties together output, input prices, and quantities. The non-linearity of production functions also imposes additional restrictions on the estimates, helping to separate the effects of technological change from those of factor substitution.

4.3 Counterfactuals Approach

In counterfactual analysis, I solve for 16 consumption allocations, c_{ijt}'s, 4 sectoral outputs, Y_{jt}'s, 4 good prices, p_{jt}'s, and 16 wages, w_{ijt}, in a system of 44 equations that describes general equilibrium of the model. The equations include 16 consumption choice equations from the household's problem (equation 3), 4 sectoral production functions (equation 13), 20 FOCs for labour and capital (equations 14-15), and 4 market clearing equations $Y_{jt} = c_{nc\,jt} + c_{rc\,jt} + c_{nm\,jt} + c_{rm\,jt}$ for sector j. This system is overidentified, as the number of equations exceeds the number of unknowns. Including the 4 additional good market-clearing equations imposes additional constraints on consumption and output solutions, ensuring that final goods are allocated consistently across households and sectors. 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.

$$\bar{\theta}_{Kj} \equiv \overline{\left[\frac{r_j K_j}{p_j Y_j}\right]} = \alpha_{Kj} \frac{\sigma_j}{\sigma_j - 1} \frac{\sigma_{Kj} - 1}{\sigma_{Kj}} \left[\exp(\gamma_{Kj}\bar{t})\overline{K}_j\right]^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} \overline{Y}_j^{\frac{1-\sigma_j}{\sigma_j}}$$

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

In equilibrium, changes in consumption arise due to DGFs, income, and relative prices. DGFs are based on an annual demand growth rate, estimated from the household's problem, and are a function of time. Household income depends on wages that are established in equilibrium. Relative prices are also an equilibrium object. Equation 3 describes household's consumption choices subject to total expenditure without using income directly. In counterfactuals, I set total expenditure to be a constant share of income equal to the average income share in the data (93.5%). This is consistent with Carroll and Summers (1991); Campbell and Mankiw (1989), who show that consumption and income growth rates are highly correlated.

In the household side of the model, I use household-level labour income, since consumption expenditures are recorded at the household level. However, in the production side of the model, labour income is measured at the individual level. To reconcile this difference, I reweigh the aggregate number of households such that the number of households is expressed in terms of individual, rather than household, incomes. For example, if the average individual income in the CPS is $50,000, and a corresponding household in the CEX data 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. 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) demonstrate that assortative mating accounts for a significant portion of cross-sectional inequality in household income. Since I aggregate expenditures at the household-type level, this reweighing does not affect the expenditure data and is solely used to align incomes in the CPS and CEX data. Matching incomes across the consumption and production data ensures that income effects are accurately captured in equilibrium. For robustness, Section **??** presents an alternative results using individual income from the CEX instead of household income, with very similar results across both measures.

Changes in production arise due to technical progress and factor supply. Technical progress is driven by factor augmenting annual technical growth rates, estimated from the sector's problem. I take factor supply at the sector level from the data when conducting counterfactual analysis. The model does not allow to solve for 16 wages and 16 labour allocations simultaneously without imposing additional structural assumptions. Thus, when performing counterfactual analysis, I treat factor allocations as given. This implies that labour distribution across sectors does not change in response to demand shifts, which could be explained through labour market frictions. Indeed, recent literature shows presence of strong labour marker 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 short and medium term, it is unlikely that there is no labour reallocation across sectors over longer periods of time. In this paper, I examine the effects of demand shifts due to DGFs over the period of 33 years. While demand shifts due to DGFs are gradual, it is possible that 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 reallocation of labour towards a sector lowers wages in the sector through the labour supply effect, as shown in equation 8. This is also why presence of labour market frictions is one of the channels that allows changes in consumption structure to affect wages and income inequality. In the presence of strong labour market frictions, and, hence, limited ability by the sector to increase good 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 the demand effects on wages arise due to labour market frictions, I conduct additional counterfactual exercises reallocating a fraction of labor based on DGFs to sectors producing goods with higher demand.

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 solves the general equilibrium taking estimates from household's and firm's problem. In the counterfactual without effects that arise due to DGFs, which I refer to as *demand effects* for the remainder of the paper, I solve for general equilibrium by setting $t = 0$ in 16 consumption allocation equations. This keeps preference structure constant at the level of 1989 throughout the analysis period. Note that DGFs affect demand for goods directly – through demand growth rates and indirectly – through non-homotheticities due to changes in income in equilibrium and prices. In the counterfactual without effects from factor augmenting technical growth rates, which I refer to as *production effects*, I solve for general equilibrium by setting $t = 0$ 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.

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, assumed in the model, at the level of the aggregate economy. I compare them with the estimates from the non-homothetic demand system, while also comparing how well the two demand system fit the data. 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 strcutural transformation literature, I estimate both specifications using data for the aggregate economy. 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 as discussed in Section 4.1.

Table 2 presents the estimation results for both CES specifications, and Figure 3 illustrates the fit of expenditure shares over time for each of the models.

The non-homothetic CES model with DGFs, denoted by the long black dashed line, outperforms the non-homothetic CES without DGFs, given by the long blue 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 routine manual expenditure share is also particularly precise. While Comin et al. (2021) highlight limitations of homothetic CES in capturing both price and income effects in long-run structural change, Figure 3 suggests that accounting for time dependent changes in demand structure, captured by DGFs, provides the model with additional flexibility and improved accuracy in modelling long-term consumption patterns.

The Akaike Information Criterion (AIC) in Table 2 corroborates this visual assessment. The AIC value is lower for the model with DGFs, indicating that it provides the better balance of model fit and parsimony. Similarly, the root mean square errors (RMSE) are lower in the model with DGFs across all goods, further supporting its superior performance.

In terms of estimated parameters, the estimate of σ 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 also differ slightly between the two models. Non-homotheticity terms also differ slightly between the two models.

The estimates in Table 2 show significant heterogeneity in demand growth rates across goods. Notably, non-routine manual intensive goods exhibit the highest annual demand growth rate (0.112), followed closely by routine cognitive intensive goods (0.110). In contrast, routine manual intensive goods have the lowest demand growth rate (0.063). The heterogeneous demand growth rates imply differential growth in demand across sectors. Sectors producing goods with higher demand growth rates are likely to experience faster demand growth, potentially leading to increased labor demand and wages in these sectors. As per equation 4, the difference between the growth rates is what drives changes in consumption structure.

When comparing estimates between the CEX (1989-2021) and NIPA (1960-2023) samples, 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. For instance, while the absolute values differ, both samples show the highest demand growth rates for non-routine manual intensive goods and routine cognitive intensive goods , with routine manual intensive goods having the lowest rates. Importantly, it is these differences in demand growth rates, rather than their absolute levels, that drive changes in consumption structure, and these differences are remarkably stable across both datasets and time periods. This consistency across different time periods and data sources provides strong validation for the results. Moreover, 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. Further, results from Monte Carlo simulations, reported in Table C.1 and Figure C.1, demonstrate that this estimation procedure consistently recovers the structural parameters of interest, particularly the differences in demand growth rates that drive changes in consumption structure.

The inclusion of DGFs in the non-homothetic CES framework offers several important implications for understanding structural change and income inequality. The significant and heterogeneous demand growth rates suggest that, aside of income and price effects, 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. DGFs provide an additional channel through which structural change can affect the distribution of labor income across sectors.

5.2 Household-level Estimates

I now turn to estimating the model for the four aggregate households.[24] This approach allows to capture heterogeneity in consumption patterns and preferences households based on their nature of work, as well as examine the extent to which incomes and income inequality are driven by changes in the household composition.

Figure 3 shows expenditure share fit of the model estimated at the household level, denoted by dashed green line. Figure A.2 shows fit of log quantity of 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, effectively capturing the non-linearities in consumption patterns over time.

Table 3 presents the estimates of subsistence levels and annual demand growth rates for each household and good. To put these estimates into perspective, Table 4 reports relative subsistence levels to household's average consumption of the 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, ranging from about 24% to 69% 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. The results reaffirm the importance 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).

[24] In the CEX data, households occupations are reported at the occupation group level. The type of the occupation group is determined based on 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.

The subsistence levels vary substantially across household types and goods. For all households, routine manual intensive (RMI) goods have the largest absolute and relative subsistence levels. This pattern suggests that these two categories include essential goods that households consume regardless of income level, albeit with different intensities across household types. For both cognitive households, the second largest subsistence level is that of non-routine cognitive intensive good, while for manual households it is the subsistence level of routine cognitive good. These differences suggest that household composition might be important for structural change arising from income effects. Both routine cognitive households also exhibit the highest absolute and relative subsistence levels across all good categories, followed by routine cognitive households. 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.

The annual demand growth rates show significant variation across goods and households. Notably, non-routine manual intensive (NMI) and routine cognitive intensive (RCI) goods consistently exhibit 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 preferences due to taste shocks (Baqaee and Burstein, 2023). Conversely, RMI goods consistently have the lowest demand growth rates. This pattern suggests a shift in consumer demand towards NMI and RCI goods over time, while shifting away from RMI 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 household are also statistically significant, reaffirming the importance of household composition in driving structural change from the demand perspective.

The heterogeneity in subsistence levels across households suggests that as incomes rise, consumption patterns will evolve differently for each household. Cognitive households, with their larger subsistence levels, may see a slower change in their consumption mix as income grows compared to manual households. The higher demand growth rates for NMI and RCI goods imply that demand for these goods is likely to increase faster than for other goods as incomes rise. This shift in demand could drive structural change towards sectors producing these goods. As a result, these sectors may see expanding demand for workers and potentially rising wages, benefiting workers in these sectors.

The inclusion of DGFs in the non-homothetic CES framework allows us to capture evolving consumer demand that drives structural change beyond traditional income and price effects. These findings have important implications for understanding the dynamics of structural transformation, and potential drivers of income inequality in the face of technological change and evolving consumer demand.

5.3 Sector-Level Estimates

Table 5 reports estimates from the production problem for the four sectors. Panel A presents estimates of factor-augmenting annual technical growth rates, providing insights into the nature of technological progress across sectors.

Across all sectors, factor augmenting technical growth rates are positive for non-routine cognitive labour, with the highest rate in the NMI sector (1.1% annually). In contrast, routine cognitive labor experiences negative technical growth rates in all sectors, with the largest decline in the RCI sector (-3.3% annually). This difference aligns with the literature on routine-biased technological change (Acemoglu and Restrepo, 2022; Goos et al., 2014; Autor et al., 2003). Both non-routine and routine manual labor generally experience negative technical growth rates, but the magnitudes are smaller compared to routine cognitive labor. This pattern suggests that while automation may be affecting manual tasks, the impact is not as severe as for routine cognitive tasks. 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.[25] Figure 4 shows Allen-Uzawa elasticities of substitution (AES) by sector. AES estimates are reported in Table A.1.

Each sector exhibits 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 Routine Cognitive Intensive (RCI) sector, the AES between non-routine manual and routine manual labor is 2.891, the highest among all elasticities. These sector-specific patterns have important implications for how technological changes and demand shifts affect the relative demand for different labour types, and

[25] 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 very similar to those obtained using CRESH production structure.

consequently, wage inequality.

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, highlighting the nuanced nature of changing consumer demand. On the production side, the sector-level estimates demonstrate 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 estimates underscore the complex interplay between evolving consumer demand and technological progress in driving structural transformation. 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 incomes across households and sectors. By comparing the baseline model with the scenario where demand effects are absent, I isolate the role of shifts in demand in shaping income distributions. I also examine the importance of preferences heterogeneity in determining the magnitude of demand effects. This analysis shows the direct effects of DGFs on income levels, as well as how changes in consumer demand interact with and, in some cases, offset the negative production-side effects due to technological change.

6.1 Main Counterfactual

Figure 5 presents the results of the main counterfactual. 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. The differences in wages between the baseline model and the counterfactual captures demand effects that arise due to DGFs.

As illustrated in Figure 5, wages for all but non-routine cognitive households are the lowest in routine intensive sectors, consistent with Acemoglu and Restrepo (2022); Goos et al. (2014); Autor et al. (2003). The middle of the income distribution includes all but non-routine cognitive households employed in non-routine intensive sectors. Finally, non-routine cognitive households remain steadily at the top of the income distribution, irrespective of their employment sector.

In the absence of demand effects, driven by DGFs, the income distribution is substantially different. Households employed in routine cognitive, RCI, and non-routine manual, NMI, sectors have lower wages – 10% lower in RCI sector, and 15% lower in NMI sector across household types. In contrast, wages of households employed in the routine manual, 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 with than baseline lower wages, followed by all but non-routine cognitive households employed in the NMI sector.

Relative ranking of all but non-routine cognitive households employed in the NCI sector in the income distribution remains the same. Households employed in the RMI sector are now closer to the top of the income distribution, with higher wages than in the baseline model. Similar to the baseline model, non-routine cognitive households are at the top of the income distribution irrespective of their sector. In this counterfactual income distribution, incomes at the bottom are lower, while incomes closer to the top of the income distribution are higher, suggesting worsening of income inequality without demand effects.

These differences in wages come from changes in prices of the goods produced by these sectors in equilibrium to match consumer demand. Figure 6 shows changes in prices over time in the baseline model and counterfactuals. The demand effects matter the most for both manual sectors, followed by routine cognitive sector. Consistent with differences in the demand growth rate estimates in Table 4 in Section 5.2, DGFs lead to an increase in prices for NMI and RCI sectors, and a decrease in price for RMI sector. Notably, demand effects seem to be as important as production effects, captured by the difference between the black and red lines in Figure 6, for both manual sectors. In both cases, changes in prices on final goods arise from demand effects rather than production effects, whereas the opposite is true for cognitive intensive sectors. Production effects are particularly large in the NCI sector.

Figure 7 shows evolution of wages over time in the baseline model and counterfactuals without demand or production effects for each of the 16 household-sector pairs. Similar to Figure 6, production effects matter the most for cognitive intensive sectors. Demand effects slightly offset the negative production effect for households in the RCI sector. In NMI sector, production effects are negative for all but non-routine cognitive households, consistent with results in Table 5 in Section 5.3. These negative effects are greatly offset by the positive demand effects, especially for manual households, where demand effects dominate production effects, resulting in higher wages. This suggests that DGFs mitigate the negative impacts of automation on these workers.

6.2 Importance of Preferences Heterogeneity

The results in Tables 3 and 4 in Section 5.2 show that preferences differ across households. Cognitive households have larger subsistence levels. Differences in the demand growth rates between RCI and NCI goods are larger for routine households compared to non-routine households, while the differences in demand growth rates between NMI and NCI goods are smaller for routine households. Non-routine cognitive households have some of the largest differences in demand growth rates, and, thus, differences in DGFs. Since incomes are determined in equilibrium, such heterogeneity in preferences could be responsible for part of the effects. Furthermore, heterogeneity in preferences also matters for long term effects, since household composition is changing over time. Over the analysis period spanning 1989-2021, 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. Figure 8 performs counterfactual analysis by keeping household composition constant at the 1989 level throughout the analysis period.[26]

The results show that up to 20% of the demand effects arise due to changes in household composition, underscoring the importance of considering changes in household demographics when exploring structural change. For RCI sector, demand effects are 8% when household composition is fixed, and 10% with varying household composition. For RMI sector, these numbers are 13% and 15%, and for NMI sector – 20% and 24% respectively. Figures A.29 and A.30 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 household, who have some of the largest DGFs, grows over time, the demand effects also become larger.

The counterfactual analysis in this Section shows that demand effects driven by DGFs play a crucial role in shaping wage distributions across sectors and households. Changing demand has particularly benefited workers in NMI and RCI sectors, partially offsetting negative production effects of labour employed in these sectors. The results also highlight the importance of preference heterogeneity across household types – up to 20% of the demand effects arise from changes in household composition over time. These findings emphasize the importance of considering both demand-side and supply-side factors, as well as the changing composition of households, when examining long-term trends in wage structures and labor market outcomes.

[26]These counterfactuals adjust only household composition from the consumption side. Labour allocations in equilibrium are the same as in main counterfactuals in Figure 5.

7 Channels of DGF Effects and Robustness

This Section explores several key channels through which DGFs influence wages and income distribution. Specifically, I focus on the role of elasticities, subsistence levels, and presence of labour market frictions and show the importance of each one of these channels in facilitating or constraining demand effects in the model.

7.1 Elasticities

This Section builds on the observation that relative consumption of two goods depends on the elasticity parameter, η, as shown in equation 4 in Section 3.2. Greater elasticity implies greater willingness to substitute between goods in response to changing DGFs, thus enabling and amplifying substitution effects that arise 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. As η increases, the model predicts stronger consumption shifts toward goods with higher demand growth rates, magnifying the influence of DGFs on consumption patterns. However, this is true up to a point, since larger η also drives the negative substitution effect due to changes in relative prices. From equation 4, as long as $e^{(\lambda_{ij}-\lambda_{im})(\eta-1)t} > \left(\frac{p_{jt}}{p_{mt}}\right)^{-\eta}$, positive effects due to demand growth rates will dominate negative price substitution effects, thus rising relative consumption. Since prices are an equilibrium object, different values of η can change the relative prices such that relative price substitution effects become greater than demand growth rate effects, leading to a decrease in relative consumption. To explore how results differ based on elasticity compared to baseline, 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 wage inequality, however, this effect is nonlinear. In the Leontief case, $\eta = 0$, there are minimal differences between the baseline model and the counterfactual without demand effects. This result is intuitive, as a zero elasticity implies that households cannot substitute between goods in response to changing DGFs. Consequently, the impact of DGFs on the wage distribution is negligible.

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 baseline model. Among the examined scenarios, the effects are the largest in the baseline model with $\eta = 2.7$. When η further increases to 4.5, the effects are smaller, suggesting that negative relative price substitution effects dominate positive effects due to demand growth rates. This is especially prominent from price counterfactuals for NMI sector, illustrated in Figure A.26.

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 in Section 5.2 shows that subsistence levels account for a substantial portion of households' consumption for all four goods. 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 can play out more fully across all income levels. This increased responsiveness can lead to larger shifts in demand across sectors, which in turn result in more pronounced wage effects.

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 general pattern of effects is consistent in both cases with and without subsistence levels.

7.3 Labour Market Frictions

In the main counterfactual analysis, I take sector level allocations of labour as given from the data. This assumes that in counterfactual scenarios labour quantities are the same in equilibrium, for example, due to strong labour market frictions (Autor et al., 2021; Hershbein and Stuart, 2020; Dustmann and Meghir, 2005). In this section, I ease this assumption by adjusting labour allocations in counterfactuals without demand effects in two ways. First, I adjust labour growth rates to keep labour distribution across sectors constant over time. Then, I adjust labour allocations based on changes in output quantities as proxies for changes in demand for final goods and, thus, labour producing these goods. Wages in the baseline model are obtained as in Section 6 without any labour market adjustments.

The first adjustment is based on preserving the distribution of labour across sectors constant in the counterfactual without demand effects. This adjustment assumes that in the baseline model labour reallocates between sectors in response to demand effects, and when the demand effects are absent, relative labour allocations would remain the same at the level of the first period in the data – 1989. This is a strong assumption, since labour allocations also depends 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. In both adjustments, I adjust labour at the sector level only, not labour type. This is because it is more likely for labour reallocation across sectors to be driven by demand effects, whereas changes in the labour structure within sectors are more likely to be driven by technological change, for example skill biased and routine biased technical change, well documented in the literature (Acemoglu and Restrepo, 2022; Goos et al., 2014; Autor et al., 2003).

I perform this adjustment using linear sector specific labour growth rates, obtained from the data on labour allocations across sectors. That is, in each period, quantity of, for example, non-routine cognitive labour employed in RMI sector is equal to the quantity of non-routine cognitive labour in RMI sector in 1989 multiplied by a linear RMI labour growth rate at time t. Labour growth rates are the same across labour types within a sector. In 2021, compared to 1989, the labour share of NCI is larger by 0.26 p.p. It is larger by 6.31 p.p. in RCI sector, 4.07 p.p. in NMI sector, and lower by 10.64 p.p. in RMI sector. To correct for these differences in the counterfactual and keep labour distribution constant over time, I set annual labour adjustment rates to -0.008% for NCI, -0.191% for RCI, -0.123% for NMI, and 0.322% for RMI sectors.The adjustment rates sum to 0, such that the size of the labour market is preserved, and only the distribution of labour across sectors changes.

Figure 11 Panel A shows that if the labour market structure remained the same as in 1989 in counterfactual without demand effects, the differences in wages between the baseline model and counterfactual are more muted, although still of the similar magnitude as the main counterfactual results. This is intuitive, since reallocation of labour towards sectors that produce higher-demanded goods will lower wages in the sector both directly through higher quantities of labour employed in the sector, and indirectly through prices for the final goods, as shown in equation 10 in Section 3.3. Higher ability of labour to shift towards higher demand growth rate sectors allows sectors to increase production, leading to more output and lower prices in equilibrium. This suggests that labour market frictions are an important channel for DGF effects on wages.

I now turn to adjusting labour quantities across sectors based on changes in demand for the final goods produced by the sectors, captured through changes in output quantities. This adjustment assumes that labour reallocates to sectors proportionally with growth in sector's output, represented by annual rates of output change. Similar to the first adjustment, it does not account for changes in production technologies, thus also being an extreme labour market reallocation scenario. To get the output change rates, I 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 factors. The trend estimates are reported in Table 7.

The average annual rate of output change, based on the trend estimates in Table 5 , is 0.775%. The differences between the good specific output change rates and the average rate determine the labour adjustment rates: -0.475% for NCI sector, 0.425% for RCI sector, 0.225% for NMI sector, and -0.175% for RMI sector I use these rates to adjust labour quantities in counterfactuals with no demand effects. The adjustment rates sum to 0, so that the size of the labour market is preserved, and only the distribution of labour across sectors changes. Under these adjustment rates, in year 2021, labour quantities in counterfactual with no demand effects are 15.68% higher in NCI sector, 14.03% lower in RCI sector, 7.43% lower in NMI sector, and 5.78% higher in RMI sector.

The estimates in Table 5 capture trends in consumption changes not just due to DGFs, but also income, prices, changes in production technologies, as well as other unobservable factors. In contrast, in the counterfactual analysis with no demand effects, I only fix DGFs to be constant across time. Thus, matching labour adjustment rates to raw annual output change rates is a sizeable labour market adjustment, substantially limiting labour market frictions, and also presenting an extreme case. Further, the labour market changes under this adjustment are substantially larger in magnitude compared to the first labour adjustment that uses labour distribution data in 1989 as a reference point.

Figure 11 Panel B shows the results using the second labour adjustment are smaller and also very robust. With largest labour adjustments, RCI and NCI sectors show larger differences in wage differences compared to main results. In the counterfactual with adjusted labour, wages are now lower for households employed in NCI sector, whereas in the main counterfactual without demand effects wage differences were negligible. In contrast, wage differences for households in RCI sector are now much smaller, since the wage effects from reallocation of labour in this counterfactual effectively counteract demand effects that arise through DGFs. The output of NCI sector in this counterfactual is also larger with more labour employed in the sector, whereas the output of RCI sector is lower, as shown in Figure A.36. These results further reinforce the importance of labour market frictions as a channel through which demand effects operate.

Similar to larger elasticity, 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 through limiting household's responsiveness in consumption allocations to DGFs. Preferences heterogeneity matters when household composition is changing over time, which is a marker of structural change. Up to 20% of demand effects occur due to changes in household distribution over time. As the share of non-routine cognitive household, who have some of the largest DGFs, grows over time, the demand effects also become larger.

8 Implications of DGF-Driven Structural Change

The counterfactual analysis shows that DGFs play a significant role in driving wages in equilibrium. This section explores the broader implications of the DGF-driven effects for income inequality, as well as discusses how the reallocation of economic activity through demand effects is related to changes in GDP growth. I begin by examining the implications of demand effects for income inequality and show how changing consumption patterns moderate the rise in income disparities over the past three decades. I then discuss whether the demand effects align with or challenge the concept of Baumol's cost disease while reaffirming that slower productivity growth in developed economies is not necessarily a negative outcome.

8.1 Income Inequality

The counterfactual analysis in Section 6 shows that 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 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.

CV in the baseline model, depicted by black line in Figure 12 Panel A, fits CV in the data, depicted by grey dashed line, over the analysis period fairly well. Blue line denotes CV in the counterfactual without demand effects. In the absence of demand effects, income inequality is higher throughout the entire period. The difference between the blue and black lines is also increasing throughout the analysis period, showing growing importance of demand effects over time. Table 7 Panel A provides a quantitative summary of these changes. The results demonstrate that in the absence of demand effects driven by DGFs, income inequality would have increased substantially more between 1989 and 2021. The change in 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, depicted by green line. That is, the green line shows what income inequality is in the scenario when preference structure and production technologies are at the level of 1989 throughout the analysis period. As shown in Figure 12 Panel B, income inequality in this case 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.[27]

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 consumption 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 decreases by 0.098 between 1989 and 2021 – 0.081 more compared to 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 due to 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 allocation of spending across goods and welfare outcomes.

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

Further, as discussed in Section 6.2, up to 20% of the demand effects arise from changes in household composition over time, particularly due to an increase in the share of non-routine cognitive households, who are also at the top of the income distribution. This suggests that the consumption patterns of these households actually contribute to limiting overall income inequality. As the share of non-routine cognitive households increases, so do demand effects that counteract negative production effects on income inequality. In a sense, rather than inequality begetting inequality, it is the case that inequality hinders inequality through demand effects.

8.2 Baumol's Cost Disease and Productivity Slowdown?

The results from the counterfactual analysis in this paper provide a new perspective on the phenomenon known as 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.[28] This shift aligns with Baumol's prediction that the economy would shift towards labour-intensive sectors where productivity improvements are more challenging to achieve. This productivity slowdown has garnered significant attention in the literature (Duernecker et al., 2017; Fernald, 2015), however, it may not necessarily be a negative outcome. As evident from Section 8.1, income inequality is lower in the presence of changing demand, and DGFs appear to be of crucial importance in offsetting widening of the income inequality due to changes in production technologies. The demand-driven reallocation of economic activity towards less productive more labour-intensive sectors[29] improves wages of workers employed in these sectors, whose wages would have been otherwise much lower due to negative effects of technological change.

This paper contributes to the growing literature that calls for reconsideration of how we interpret and measure economic progress in developed economies, highlighting the complex interplay between changing consumption patterns, productivity growth, and structural change. The results in this paper align with the argument put forward by Vollrath (2020), who contends that slower GDP growth in developed economies is largely

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

$$F_j(K_{jt}, \mathbf{L_{jt}}) = e^{\gamma_j t}\Big[\alpha_{Kj}(K_{jt})^{\frac{\sigma_{Kj}-1}{\sigma_{Kj}}} + \sum_{\substack{i=nc,\, rc,\\ nm,\, rm}} \alpha_{Lij}(L_{ijt})^{\frac{\sigma_{Lij}-1}{\sigma_{Lij}}}\Big]^{\frac{\sigma_j}{\sigma_j - 1}} \tag{16}$$

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

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

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 recent literature questioning the negative connotations often 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 with DGFs, the higher DGFs in NCI sector, for example, could be reflecting such unmeasured quality improvements or increased consumer valuation of these goods and services. For instance, the computing power of a laptop has increased dramatically over the analysis period. As production of technologies becomes more evolved and time-consuming due to increased quality of the goods, in the data this appears as decreased productivity, which is not necessarily the case. 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. To what extent this is the case remains a fruitful avenue for future research.

9 Conclusion

This paper provides new insights into the dynamics of income inequality by examining the role of evolving consumer demand alongside technological change. 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.

One contribution of the paper is the development of 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 1989-2021 period in ways not fully captured by income or price effects alone.

Counterfactual analysis demonstrates 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 non-routine manual intensive (NMI) and routine cognitive intensive (RCI) sectors, partially offsetting negative production effects for households employed in these sectors. The magnitude of these demand effects is substantial – the effects of changing demand on income inequality nearly match those of technological change, but in the opposite direction.

The paper also highlights the importance of preferences heterogeneity across households. Up to 20% of the DGF-driven demand effects arise from shifts in household composition over time, particularly the increase in non-routine cognitive households. Counterintuitively, 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 advanced 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 a negative outcome 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 deeper insights into the nature of evolving consumer demand. Second, extending the model to incorporate more detailed labor market dynamics and potentially endogenous labour reallocation across sectors could refine our understanding of how demand shifts translate into wage effects. 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 complex interplay between technological progress and consumer demand in advanced economies.

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Figures and Tables

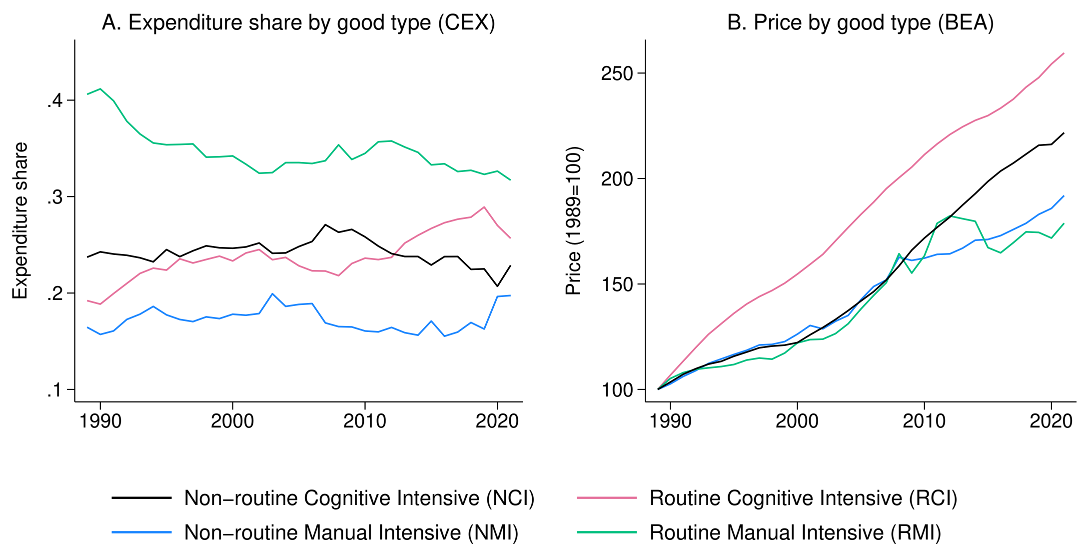

Figure 1: Expenditure Shares and Prices by Good Type

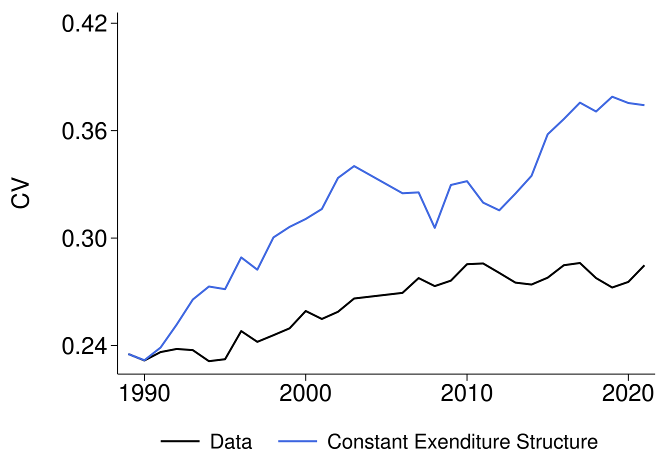

Figure 2: Coefficient of Variation Over Time

Note: CV – coefficient of variation. Constant expenditure structure coefficient of variation 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.

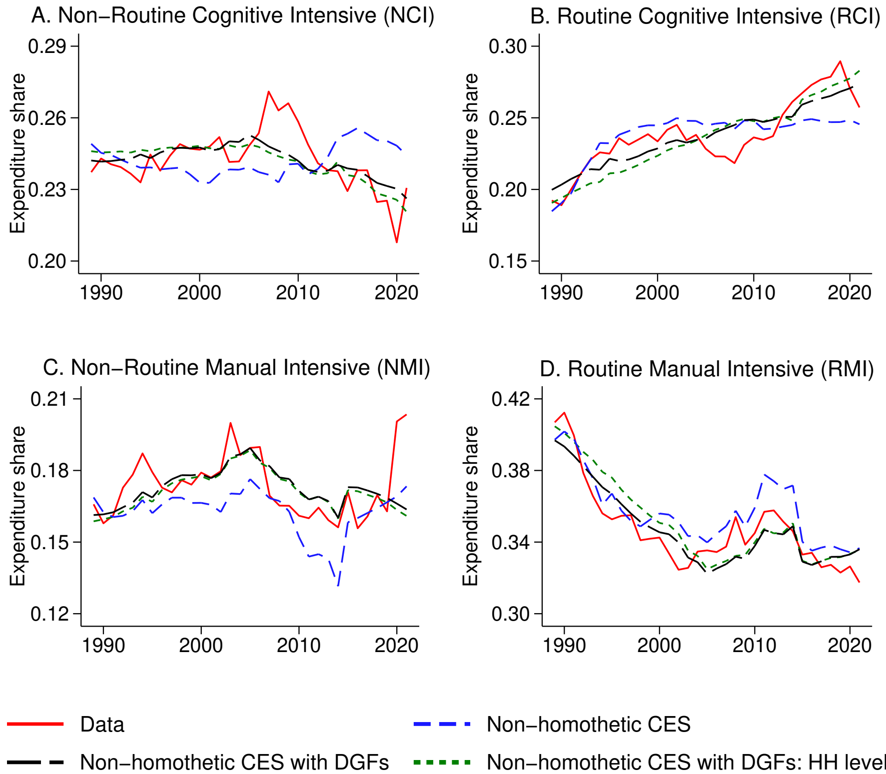

Figure 3: Fit of Aggregate Expenditure Shares by Good

Note: Estimates are obtained using aggregated data at the quarter-year level from a demand system consisting of FOCs for three expenditure shares – non-routine cognitive intensive, routine cognitive intensive, and routine manual intensive good shares using iterated FGLS. Equation for expenditure share of routine manual intensive good was dropped to avoid a singular error covariance matrix. The estimated FOCs for each utility function specification are in Table 1. Estimates used to get fitted shares are reported in Tables 2 and 3.

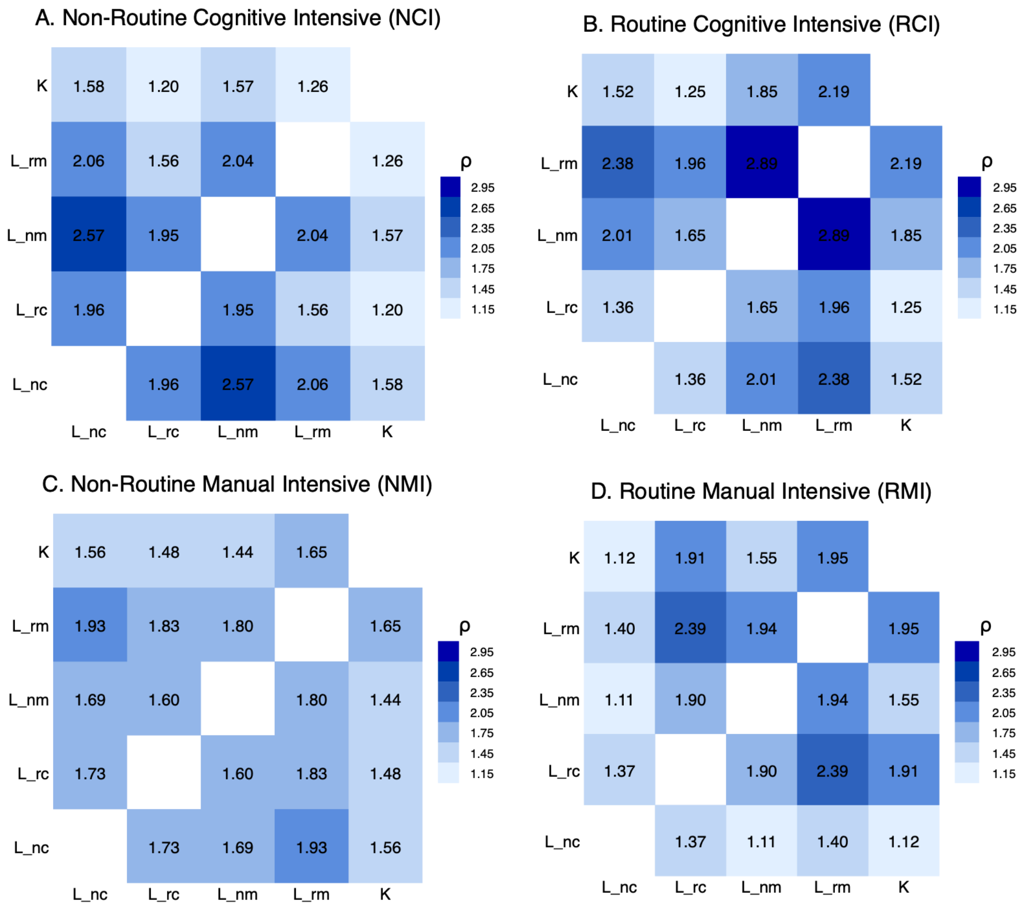

Figure 4: Allen-Uzawa Factor-Pair Elasticities of Substitution by Sector

Note: Allen-Uzawa elasticities (AES) are calculated based on equation 7 using CRESH elasticity estimates from Table 4. Table A.1 reports all AES and their standard errors.

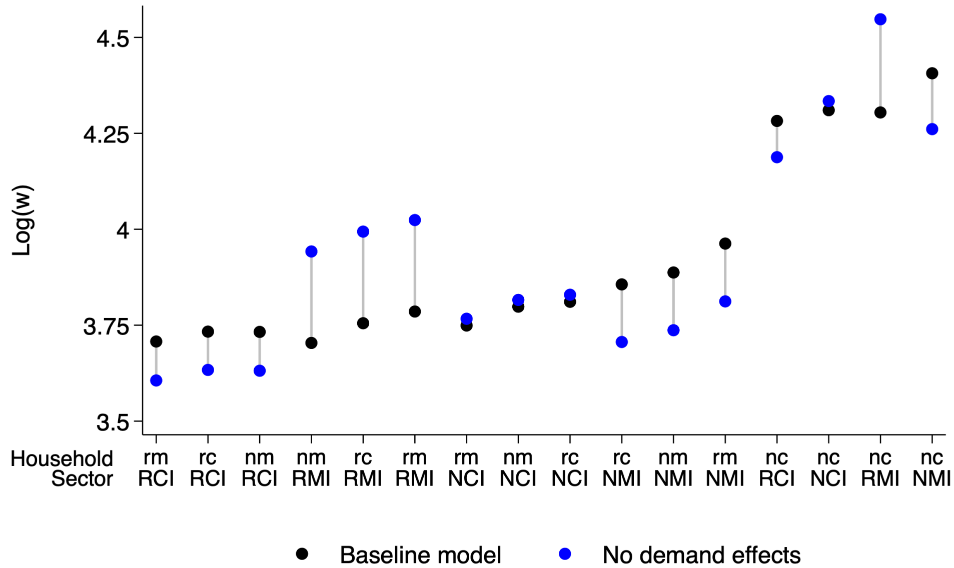

Figure 5: Wages In the Baseline Model and Counterfactual Without Demand Effects in 2021

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. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects. Figure A.20 illustrates wages in the baseline model and counterfactual with no demand effects pre-Covid for the year 2019.

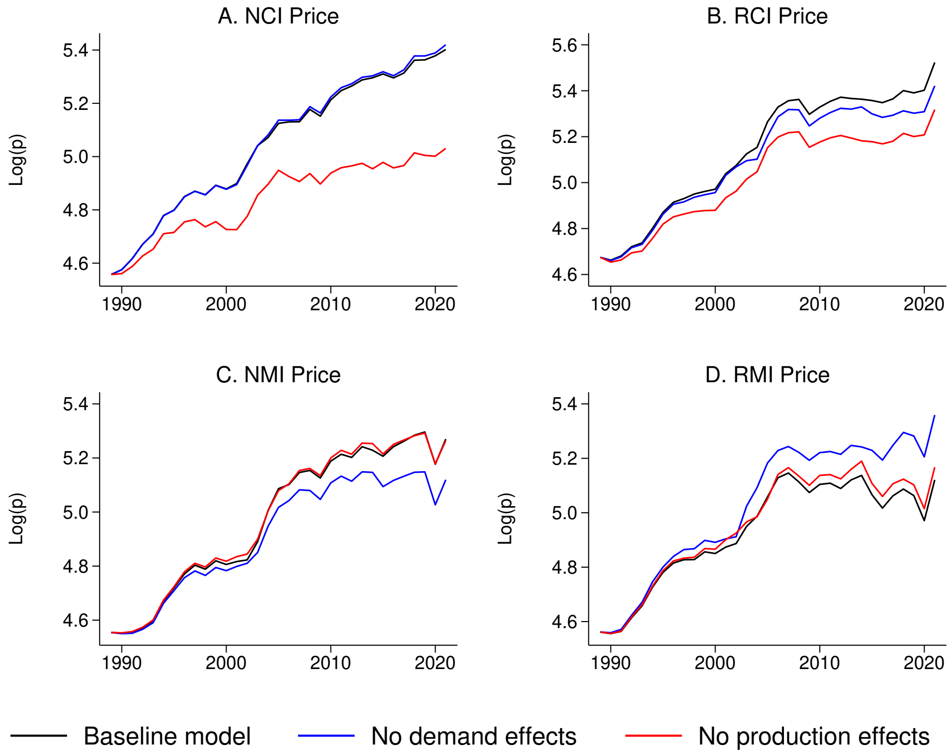

Figure 6: Prices In the Baseline Model and Counterfactual Without Demand Effects Over Time

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. Counterfactual without demand effects shows wages in equilibrium without DGF effects.

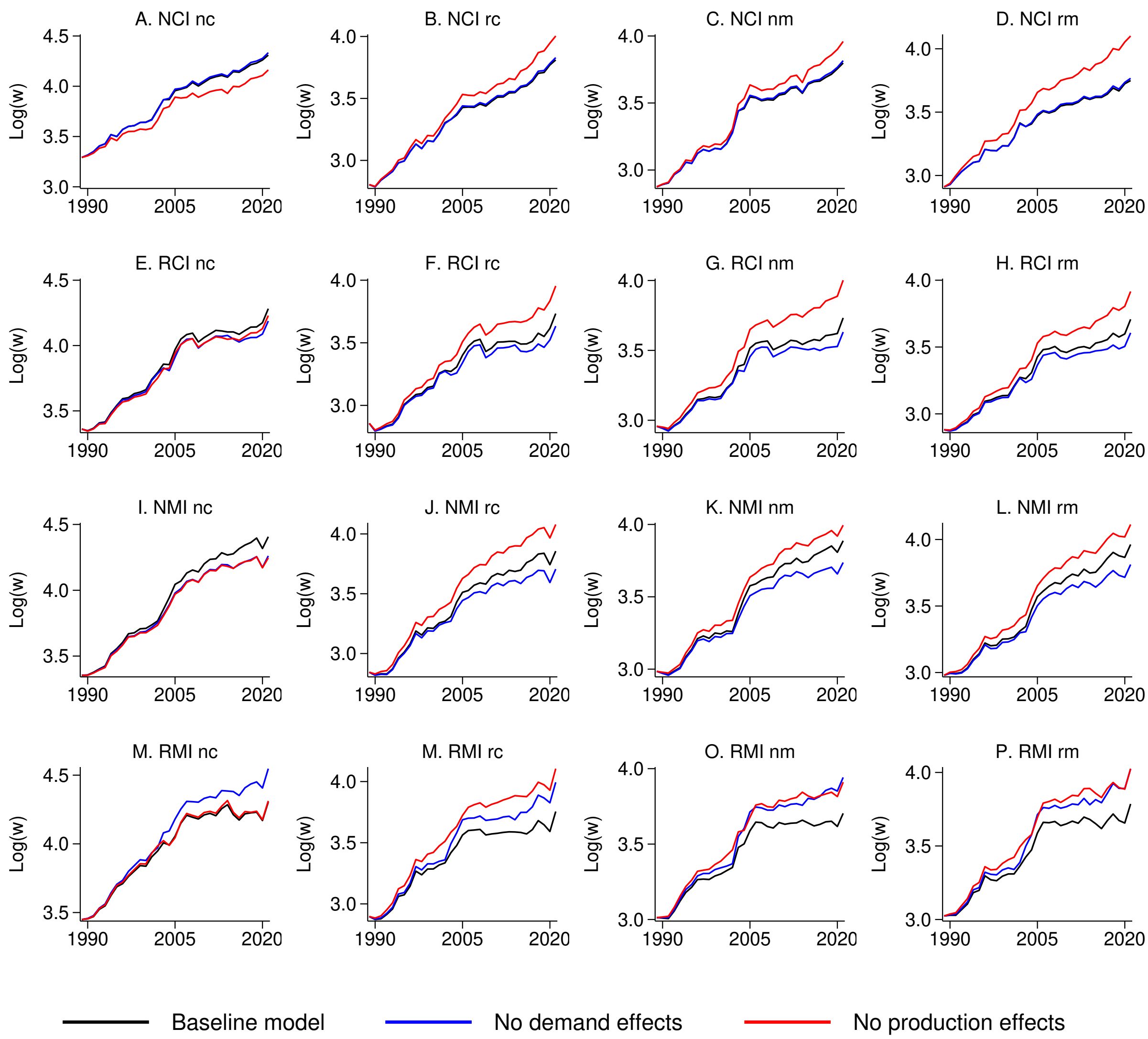

Figure 7: Wages In the Baseline Model and Counterfactual Without Demand Effects Over Time

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. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects.

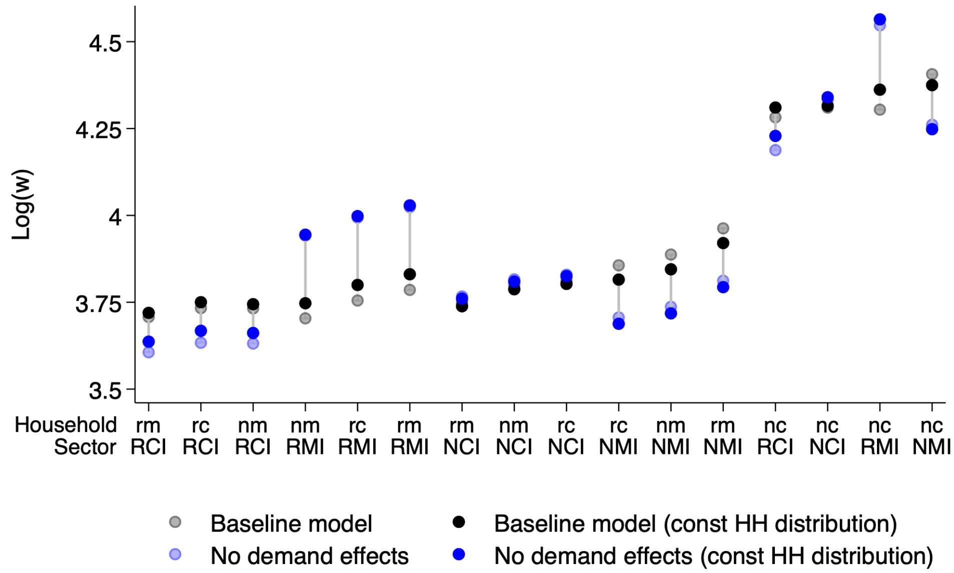

Figure 8: Wage Differences in 2021 with Constant Household Distribution

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. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects. Wage differences over time are illustrated in Figure A.29.

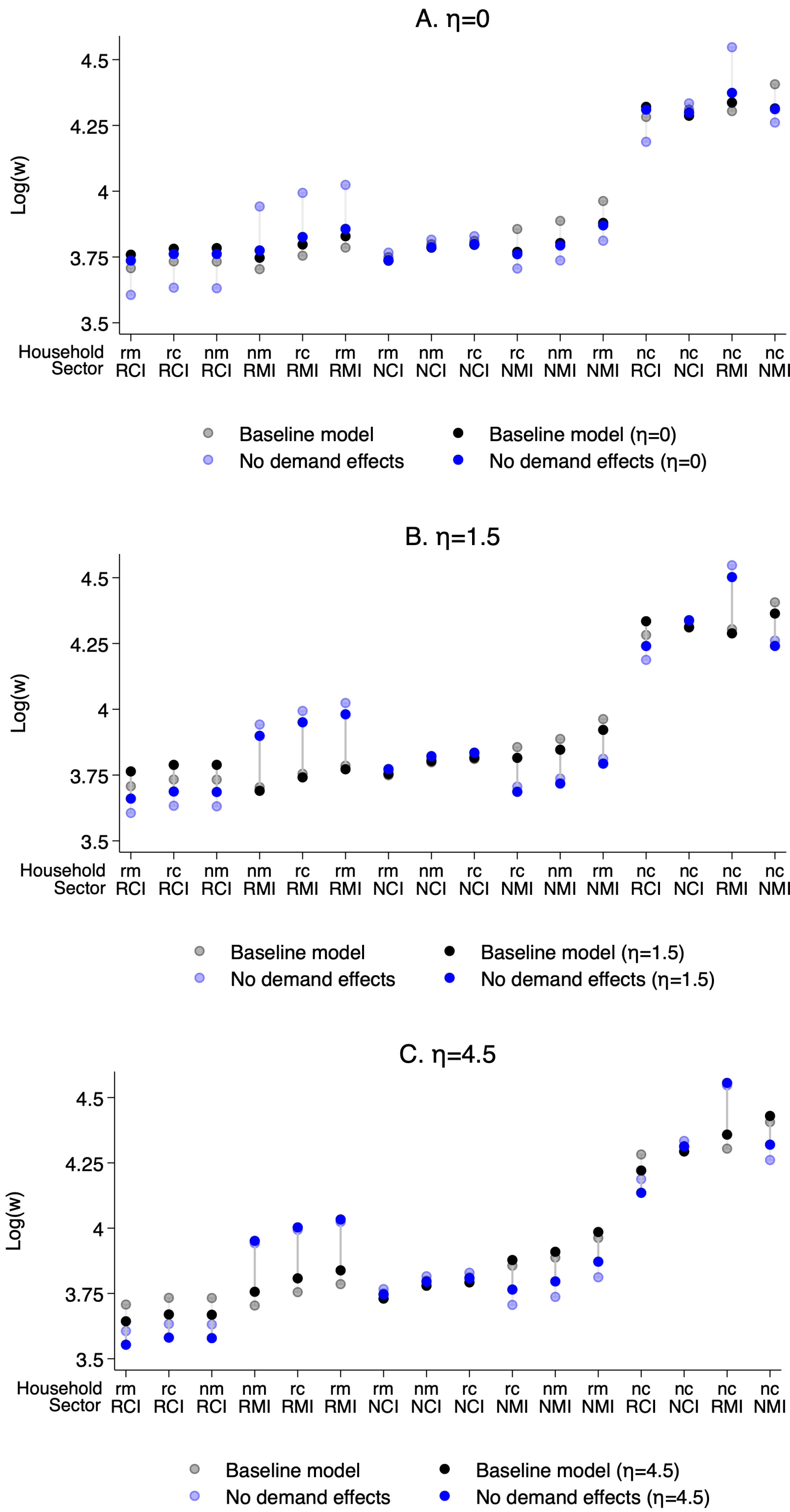

Figure 9: Wage Differences in 2021 For Varying Elasticity

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. Wage differences over time are illustrated in Figures A.21-A.25.

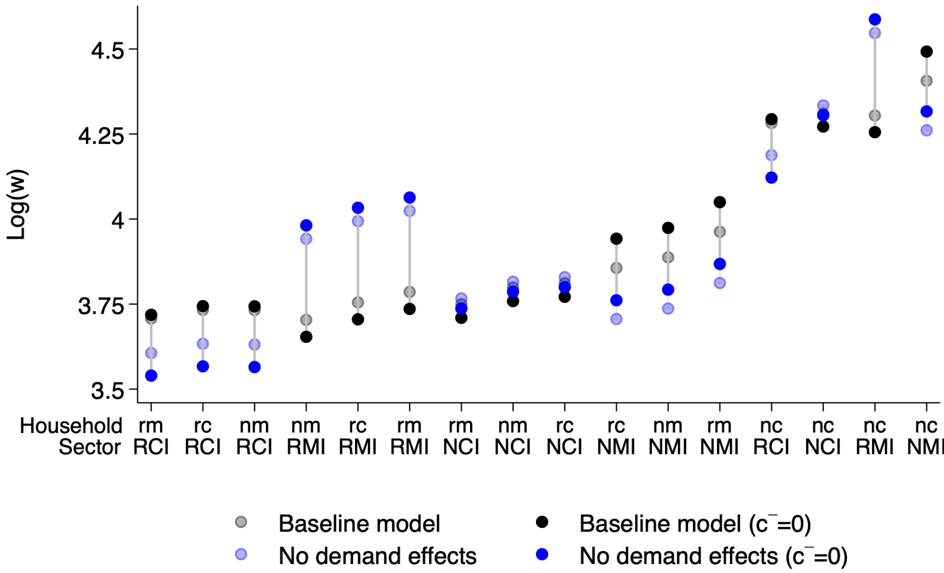

Figure 10: Wage Differences in 2021 with no Subsistence levels

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. Counterfactual without demand effects shows wage distribution that arises in the absence of DGF effects. Wage differences over time are illustrated in Figure A.27.

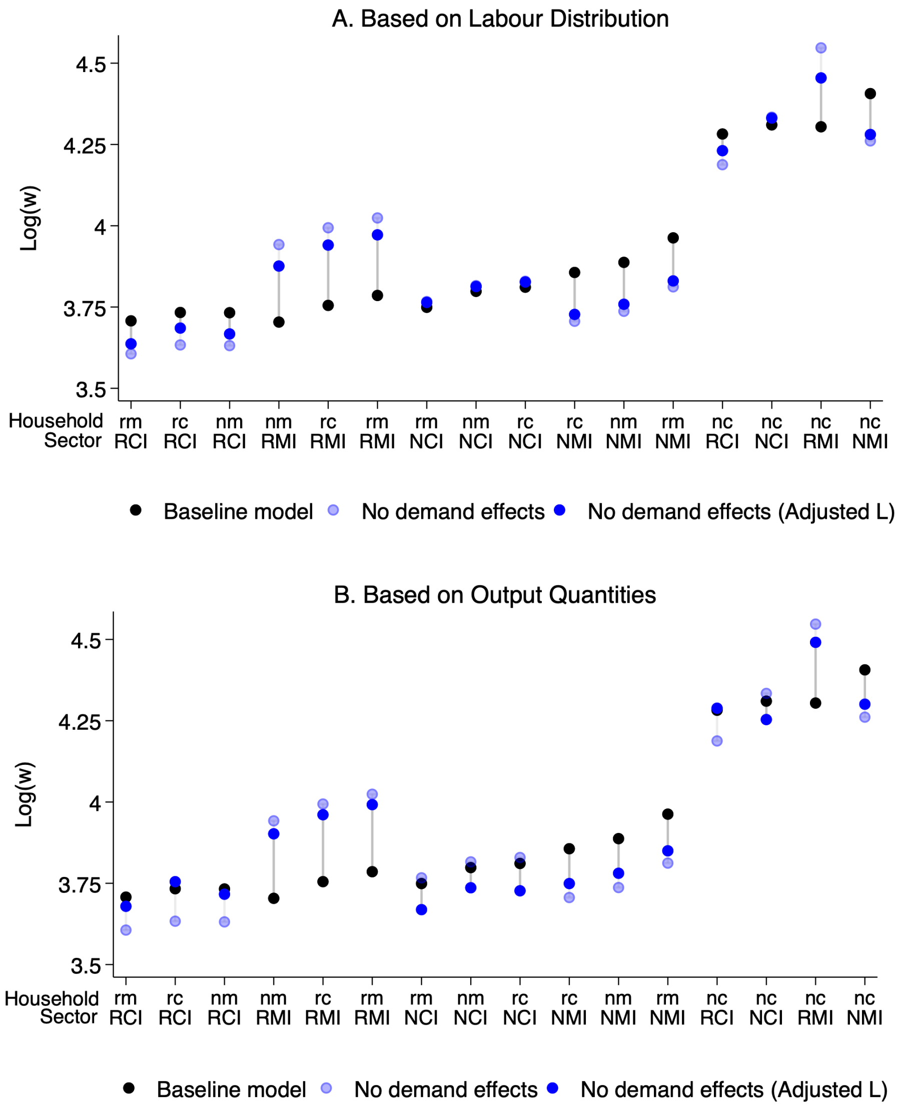

Figure 11: Wage Differences in 2021 For Adjusted Labour Allocations

Note: Panel A keeps labour distribution constant at the level of 1989 for all years by scaling labour with sector specific labour adjustment rate. Panel B adjusts labour allocations 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. Wage differences over time are illustrated in Figures A.31 and A.34.

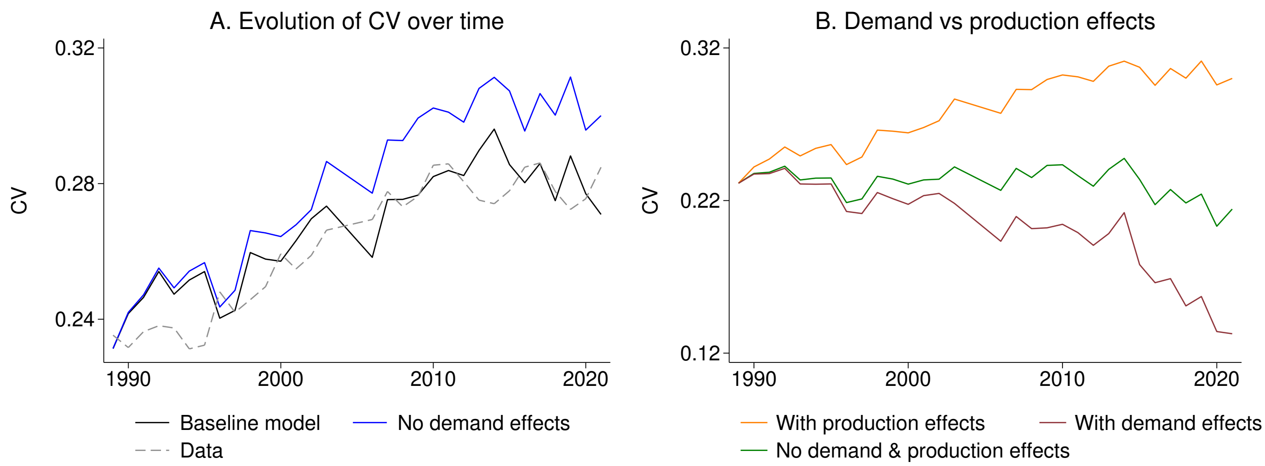

Figure 12: Coefficient of Variation Over Time in the Baseline Model and Counterfactuals

Note: Coefficient of Variation (CV): $CV = \frac{SD_{Income}}{Average\ Income}$. With demand effects line plots CV from a counterfactual that allows DGF effects to change over time as in the baseline model but keeps factor augmenting technical growth rates constant at the level of 1989, i.e. the no production effects counterfactual. With production effects line plots CV from counterfactual that keeps DGF effects constant at the level of 1989 and only allows factor augmenting technical change to occur, i.e. the no demand effects counterfactual. Green line plots CV from the counterfactual that keeps both DGFs and factor augmenting technical growth at the level of 1989. Years 2004 and 2005 are excluded from the Figure since they do not include unimputed salary, as discussed in Appendix B.

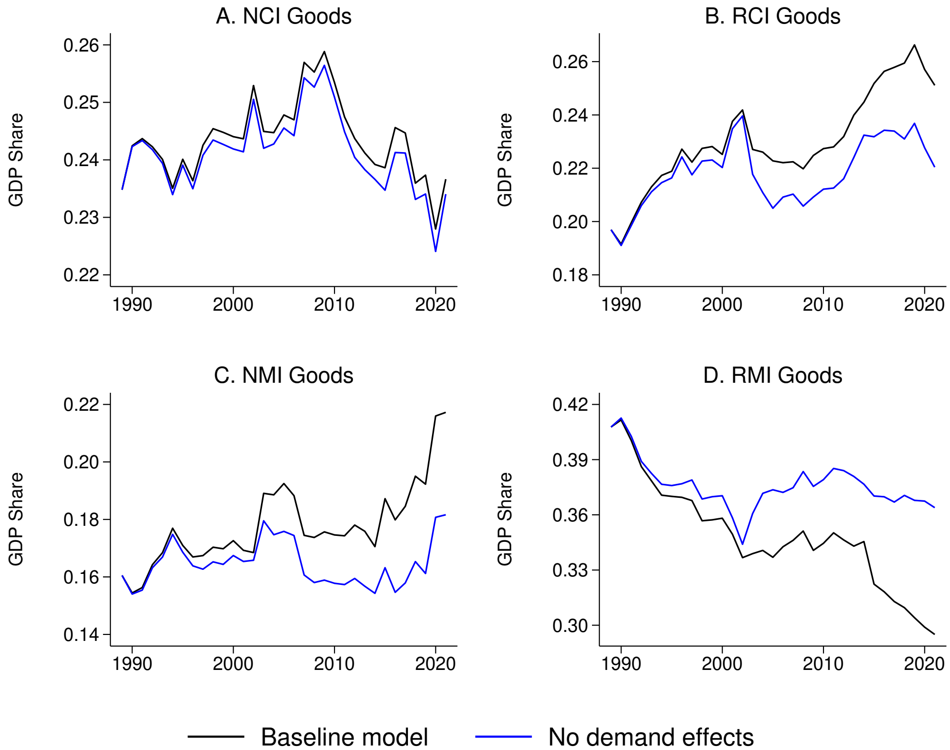

Figure 13: Evolution of Gross Domestic Product Shares Over Time in the Baseline Model and Counterfactual Without Demand Effects

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

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

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

Note: 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 using iterated FGLS, as described in Section 4.1. Equation for expenditure share of routine manual intensive 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, 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, 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[a]			
$\bar{c}_{NCI}/c_{NCI}$	-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: [a] Subsistence levels relative to average consumption quantities are reported in absolute terms. Panels A and B are based on estimates from Table 3. Standard errors are in parentheses. Standard errors for $\bar{c}_j/c_j$ are from 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 based on quarter-year data from the system of 24 equations, given by equations 13-15 for each sector. Estimation is done using non-linear 3SLS, as described in Section 4.2. 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 rate of output change			
δ_j	0.003	0.012***	0.010***	0.006**
	(0.003)	(0.002)	(0.003)	(0.002)
	Panel B: Differences in output rate change compared to average			
$\overline{\delta}$	0.008			
$\delta_j - \overline{\delta}$	-0.005	0.004	0.002	-0.002

Note: Estimates are based on OLS regressions given by $log(c_{jt}) = \beta + \delta t + e_{jt}$, where t is the trend variable. 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: Coefficient of Variation (CV): $CV = \frac{SD_{Income}}{Average\ Income}$. With demand effects only CV is taken from the counterfactual that allows DGF effects to change over time as in the baseline model but keeps factor augmenting technical growth rates constant at the level of 1989, i.e. the no production effects counterfactual. With production effects only CV is taken from the counterfactual that keeps DGF effects constant at the level of 1989 and only allows factor augmenting technical change to occur, i.e. the no demand effects counterfactual. No demand and production effects counterfactual keeps both DGFs and factor augmenting technical growth at the level of 1989.

Appendix A: Supplementary Figures and Tables

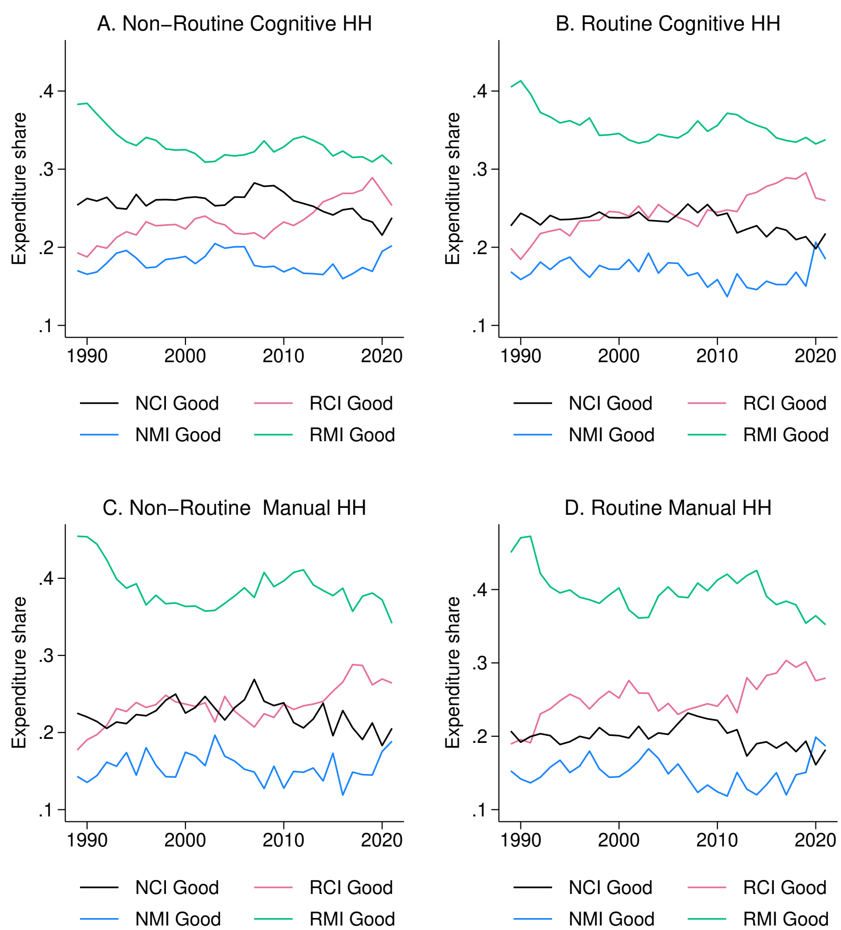

Figure A.1: Expenditure shares by Good Type Across Households

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

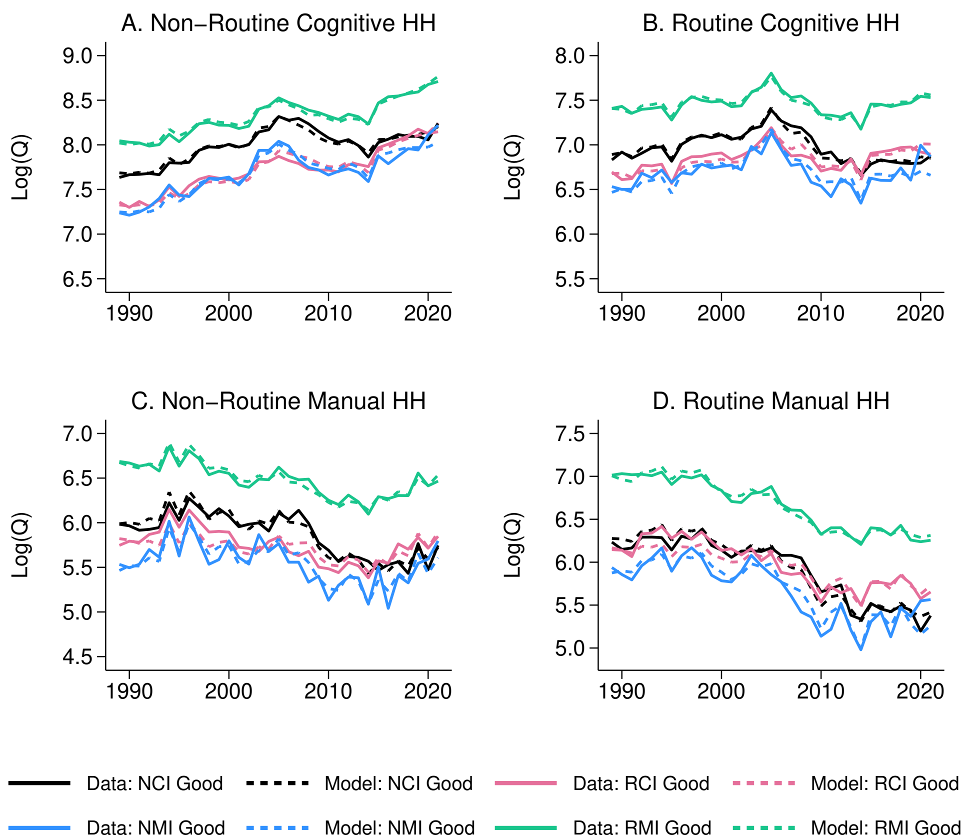

Figure A.2: Fit of Log Quantities Consumed by Households

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.

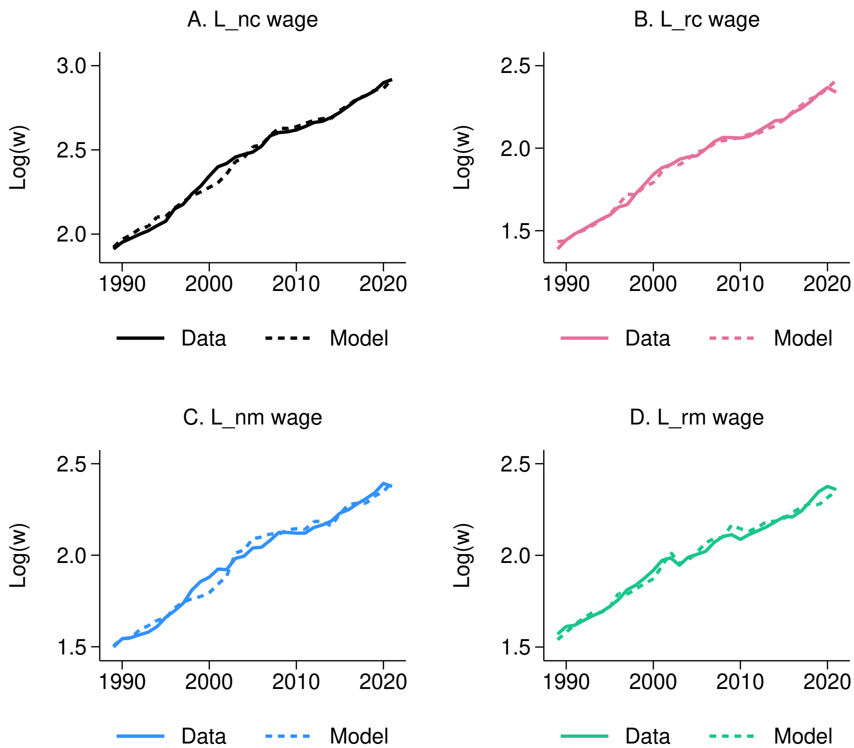

Figure A.3: Wages for Non-Routine Cognitive Intensive (NCI) Sector by Labour Type

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.

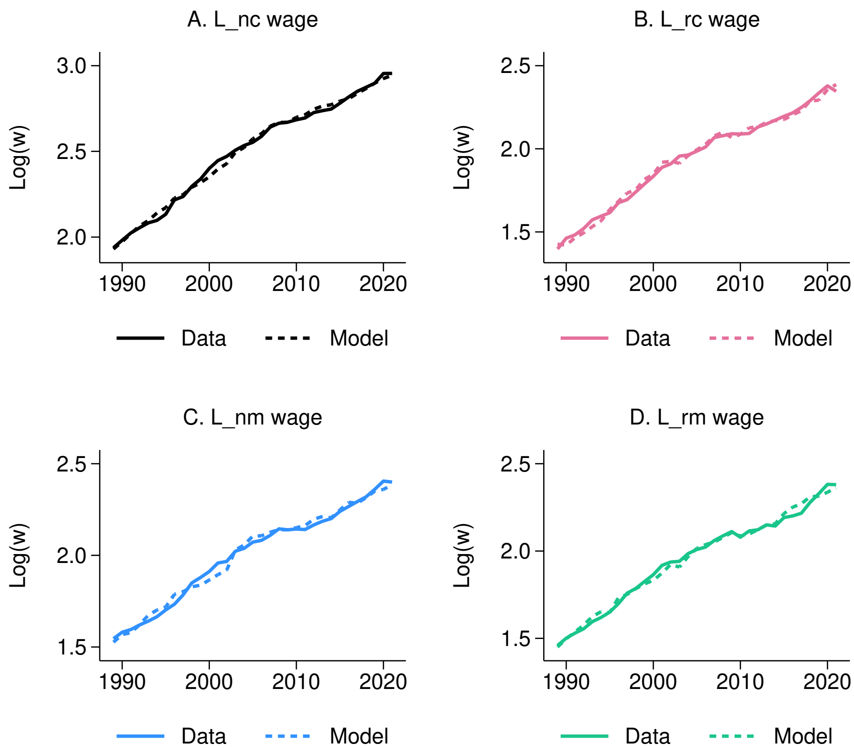

Figure A.4: Wages for Routine Cognitive Intensive (RCI) Sector by Labour Type

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.

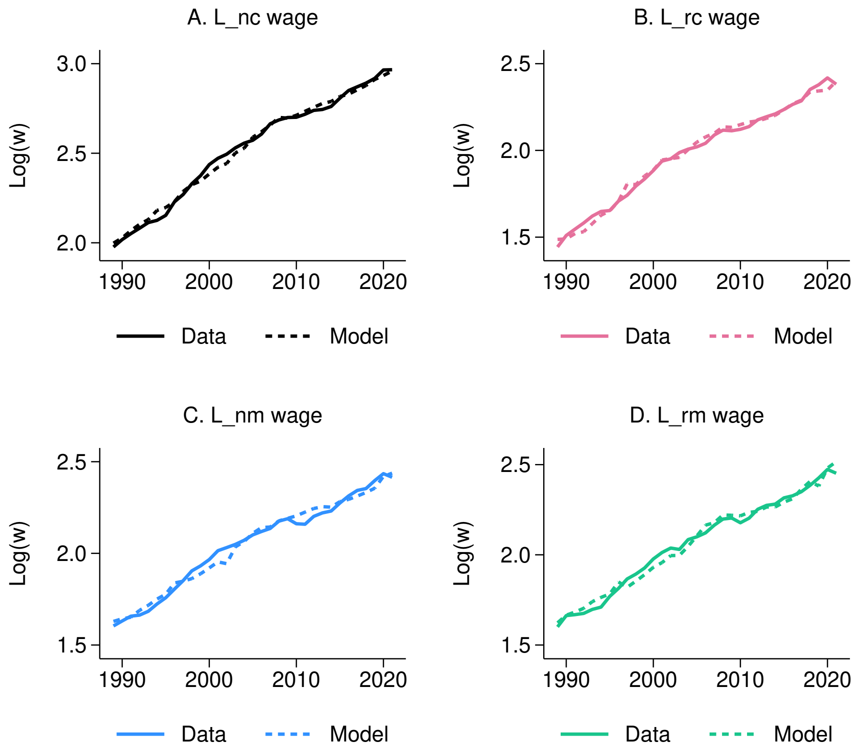

Figure A.5: Wages for Non-Routine Manual Intensive (NMI) Sector by Labour Type

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.

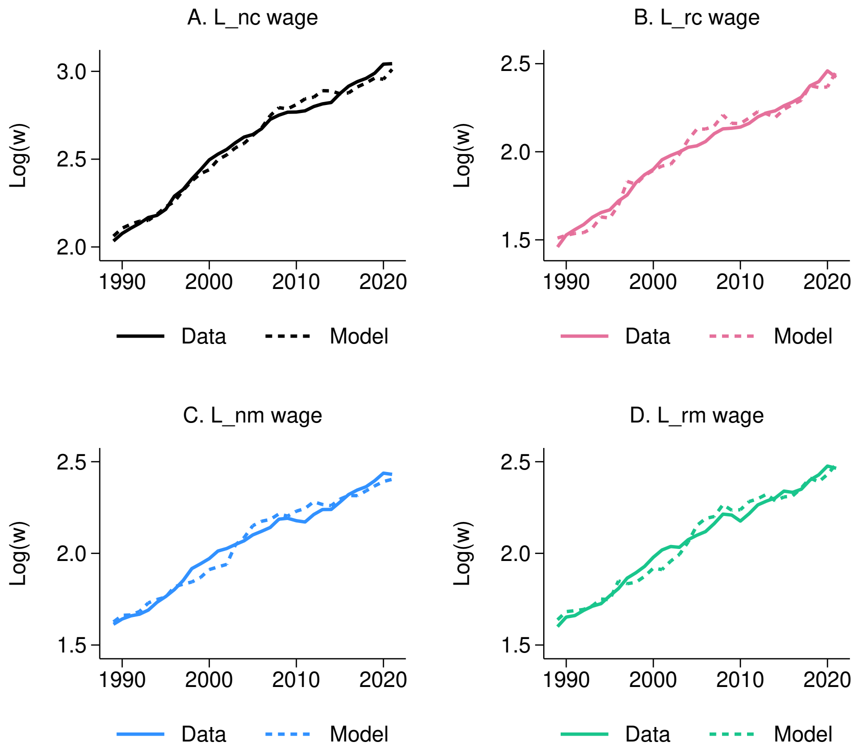

Figure A.6: Wages for Routine Manual Intensive (RMI) Sector by Labour Type

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.

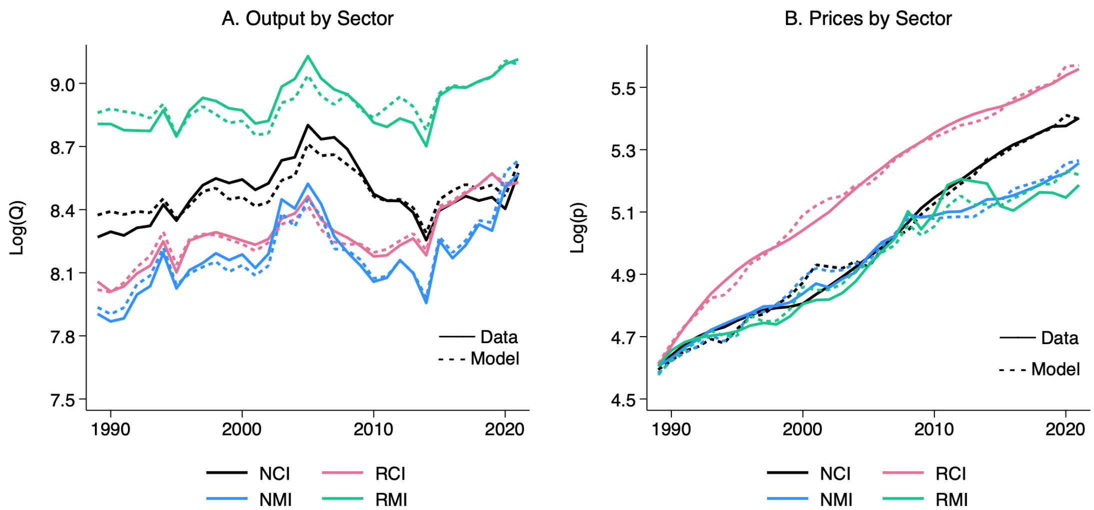

Figure A.7: Output and Prices by Sector

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.

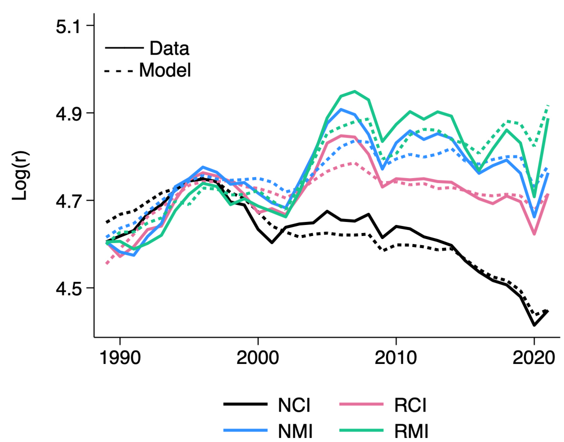

Figure A.8: Rent by Sector

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.Figure 4 plotsl 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 sector specific σ's. Estimation is done using non-linear 3SLS, as described in Section 4.2. Standard errors are in parentheses. * p<0.10 ** p<0.05 *** p<0.01.

Data Fit Figures from Counterfactual Analysis at the Household Level

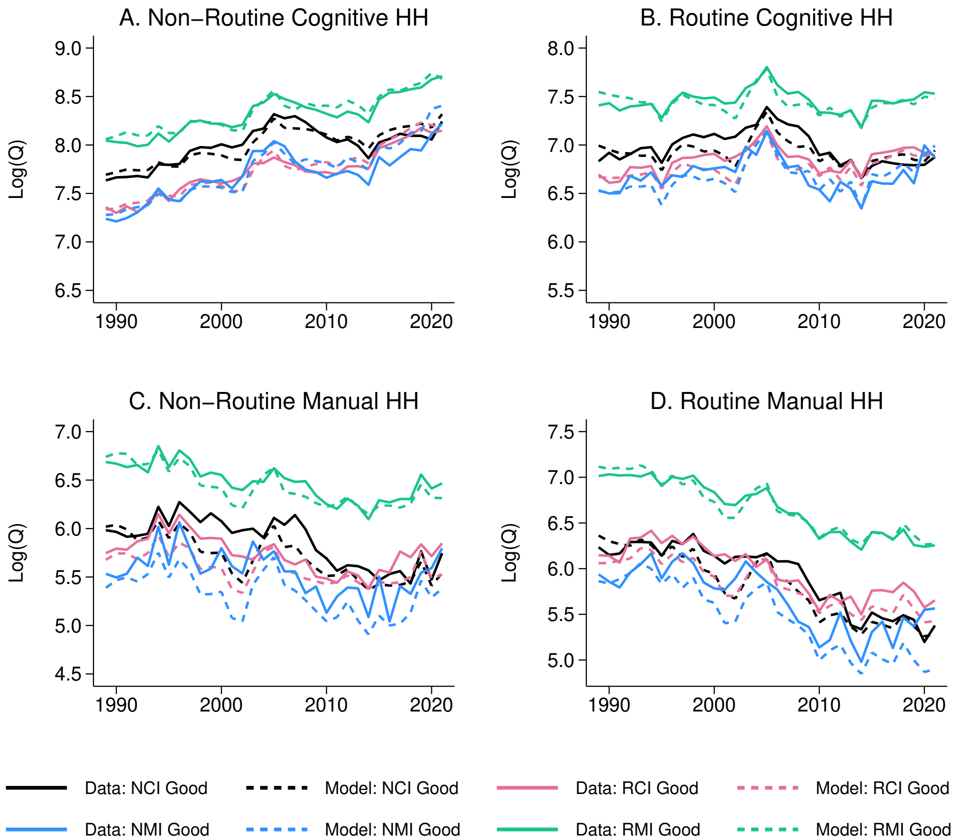

Figure A.9: Household-Level Consumption: Counterfactual Baseline Model Data Fit

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

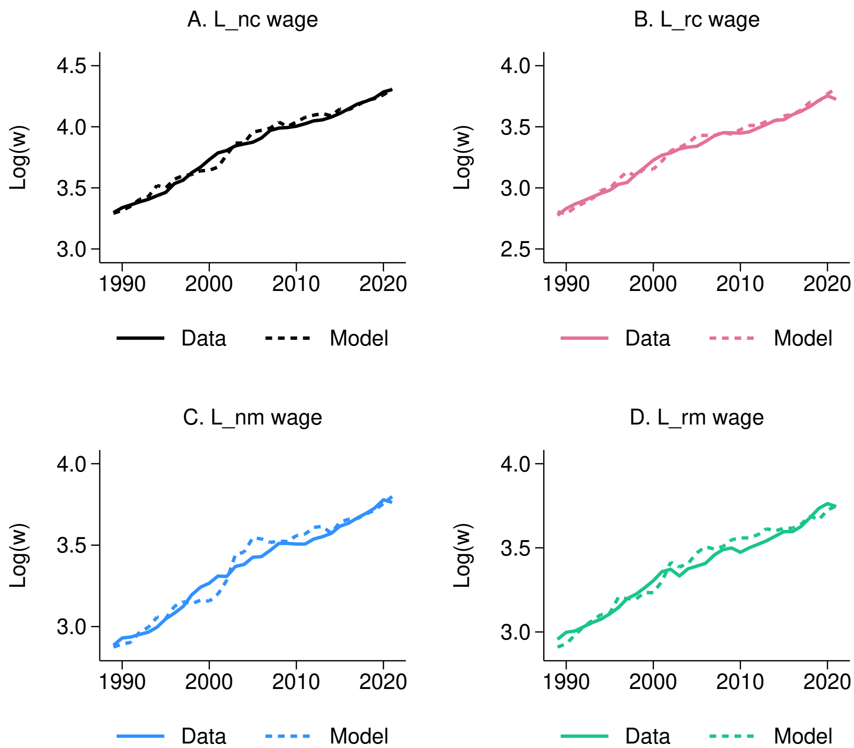

Figure A.10: Wages for Non-Routine Cognitive Intensive (NCI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

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.

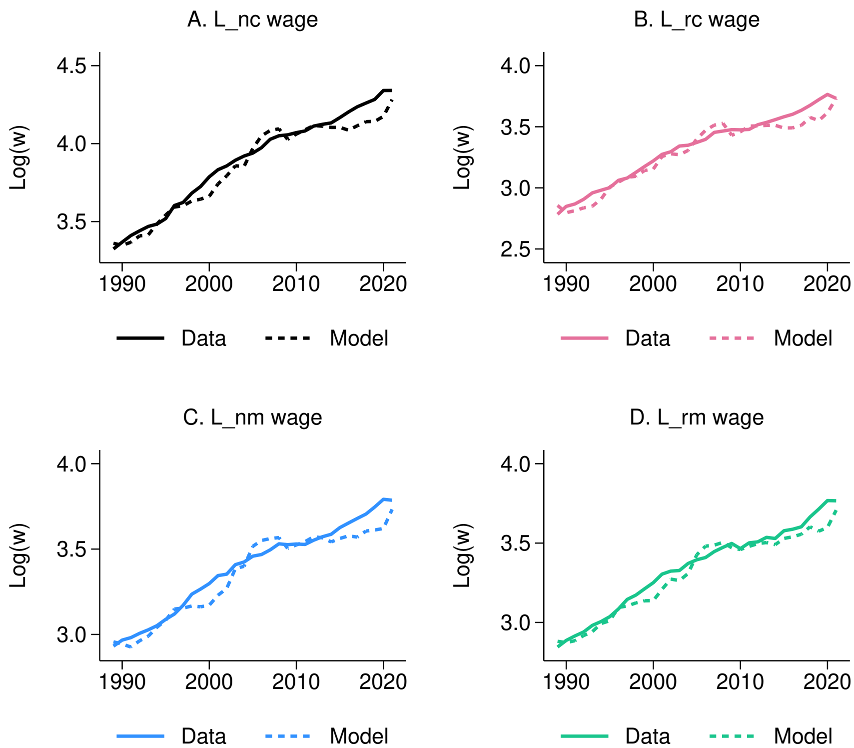

Figure A.11: Wages for Routine Cognitive Intensive (RCI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

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.

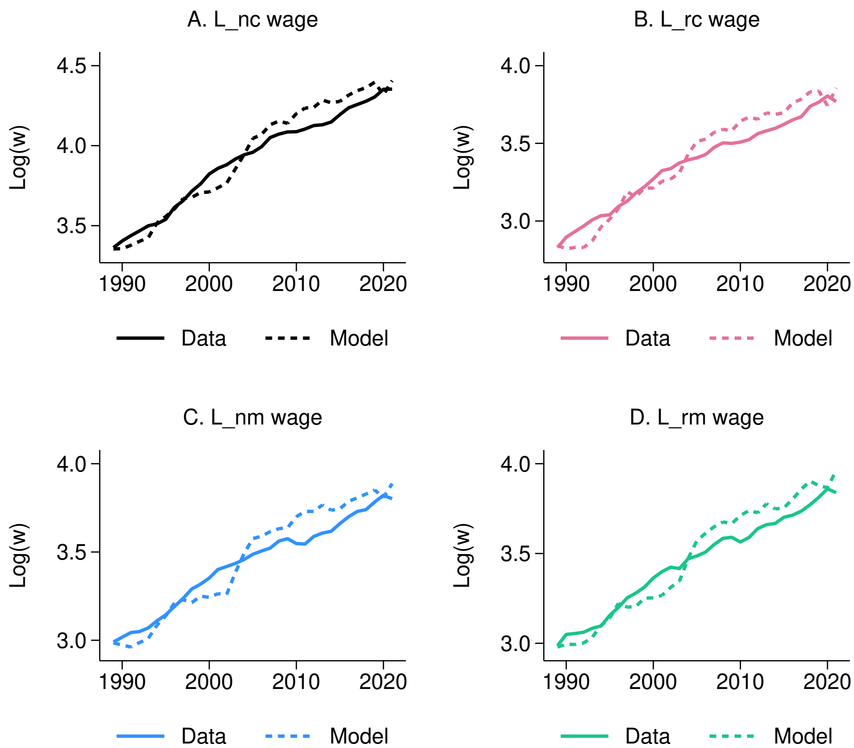

Figure A.12: Wages for Non-Routine Manual Intensive (NMI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

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.

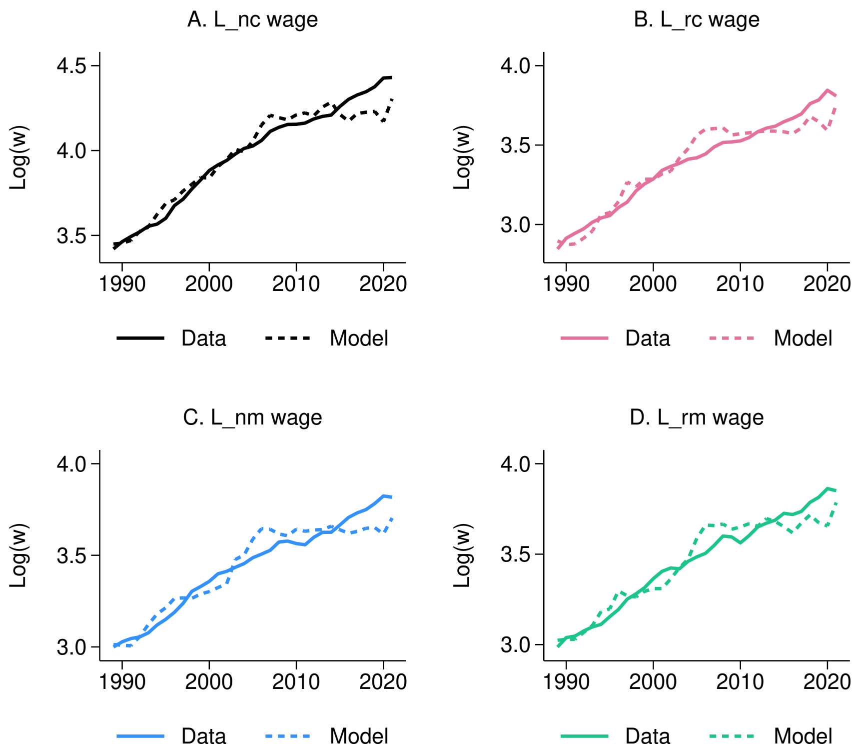

Figure A.13: Wages for Routine Manual Intensive (RMI) Sector by Labour Type: Counterfactual Baseline Model Data Fit

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.

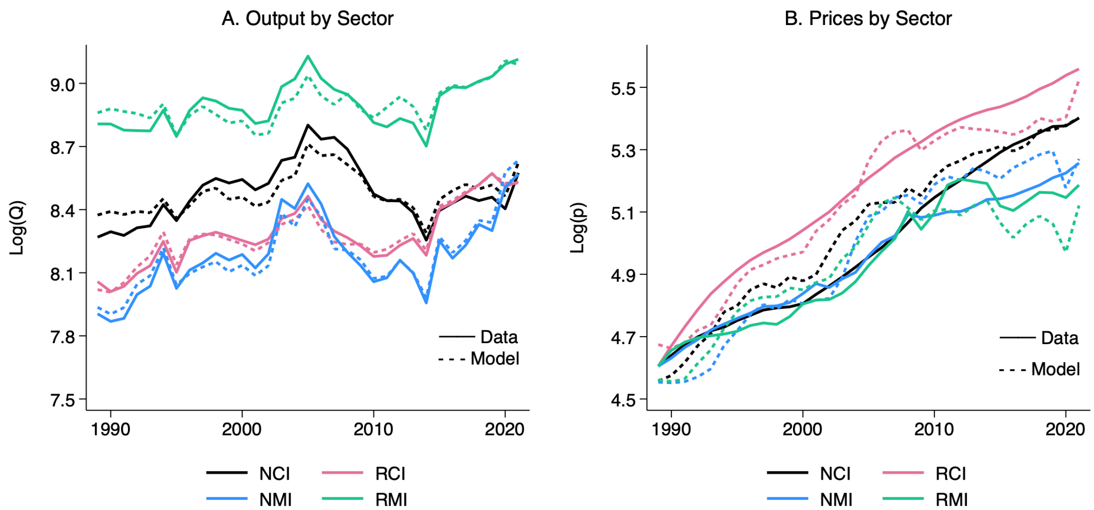

Figure A.14: Output and Prices by Sector

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

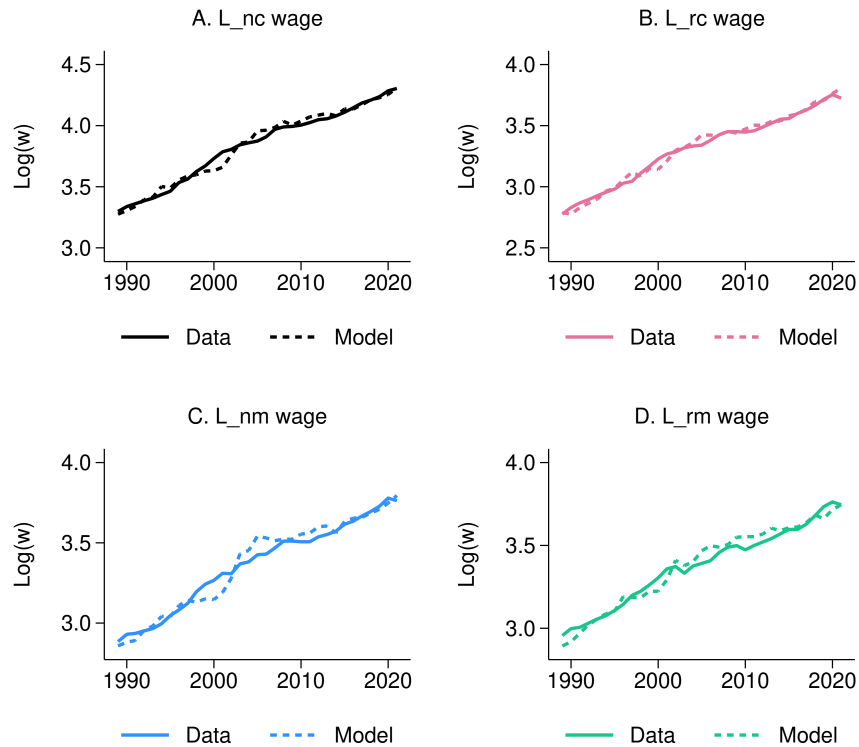

Figure A.15: Wages for Non-Routine Cognitive Intensive (NCI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

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.

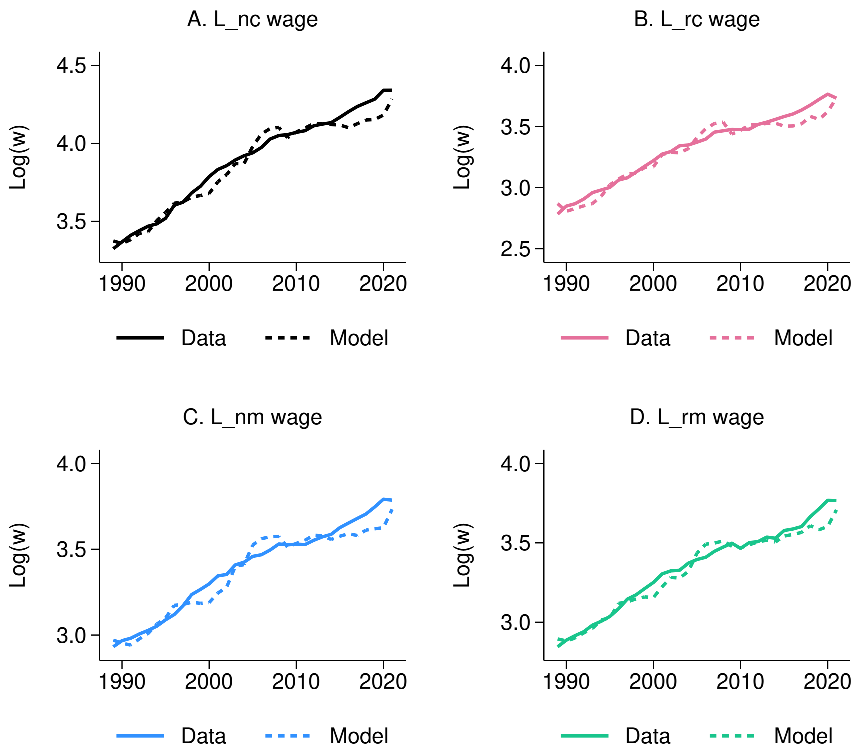

Figure A.16: Wages for Routine Cognitive Intensive (RCI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

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.

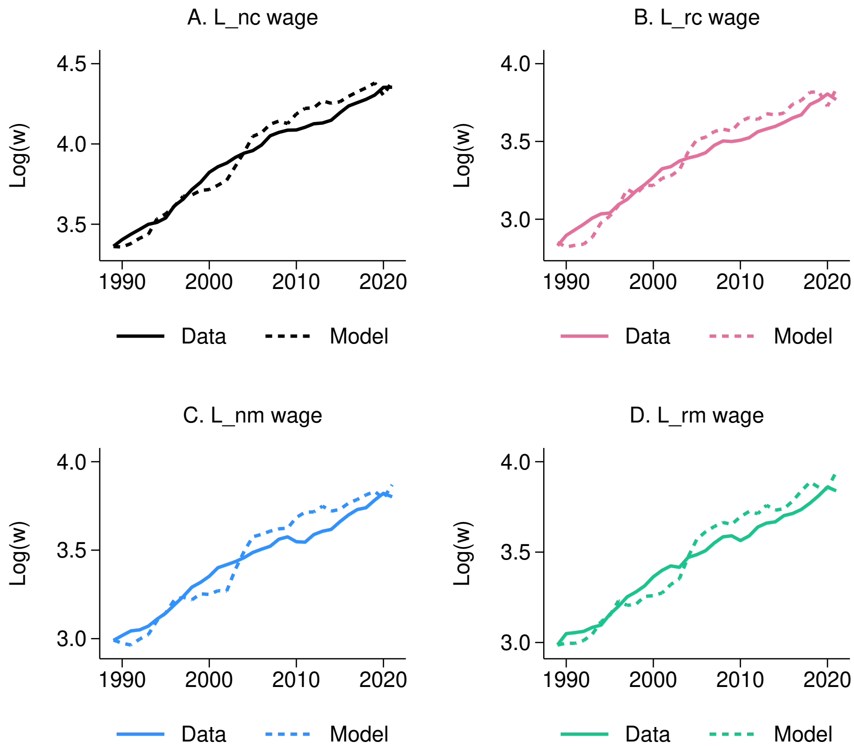

Figure A.17: Wages for Non-Routine Manual Intensive (NMI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

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.

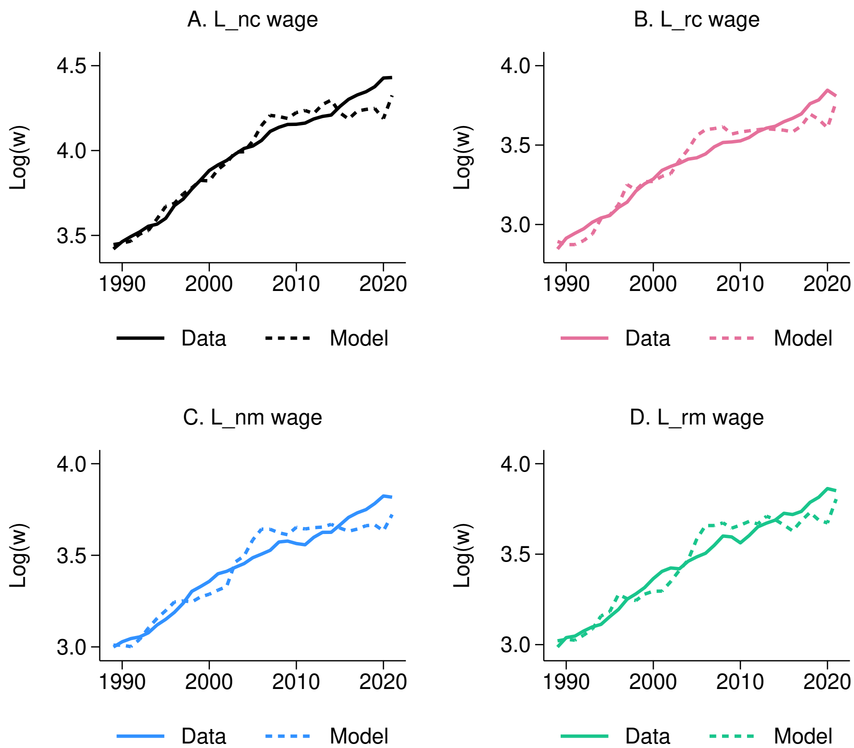

Figure A.18: Wages for Routine Manual Intensive (RMI) Sector by Labour Type: Aggregate Economy Counterfactual Baseline Model Data Fit

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.

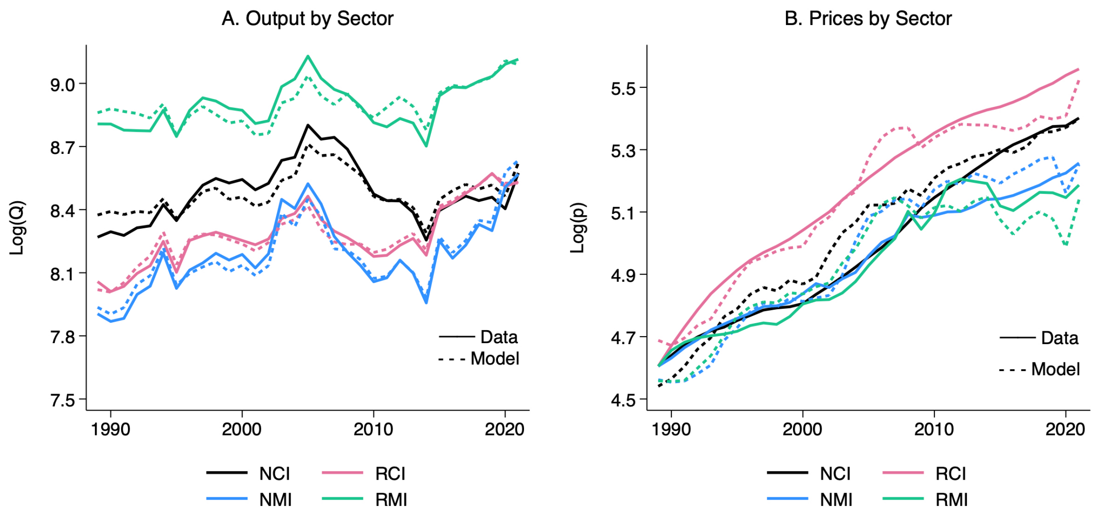

Figure A.19: Output and Prices by Sector: Aggregate Economy Counterfactual Baseline Model Data Fit

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

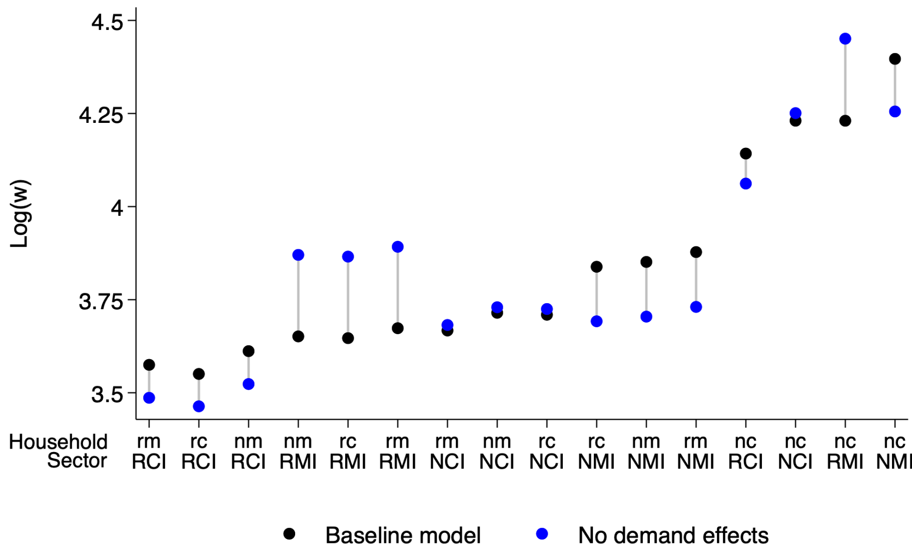

Figure A.20: Wages In the Baseline Model and Counterfactual Without Demand Effects in 2019

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.

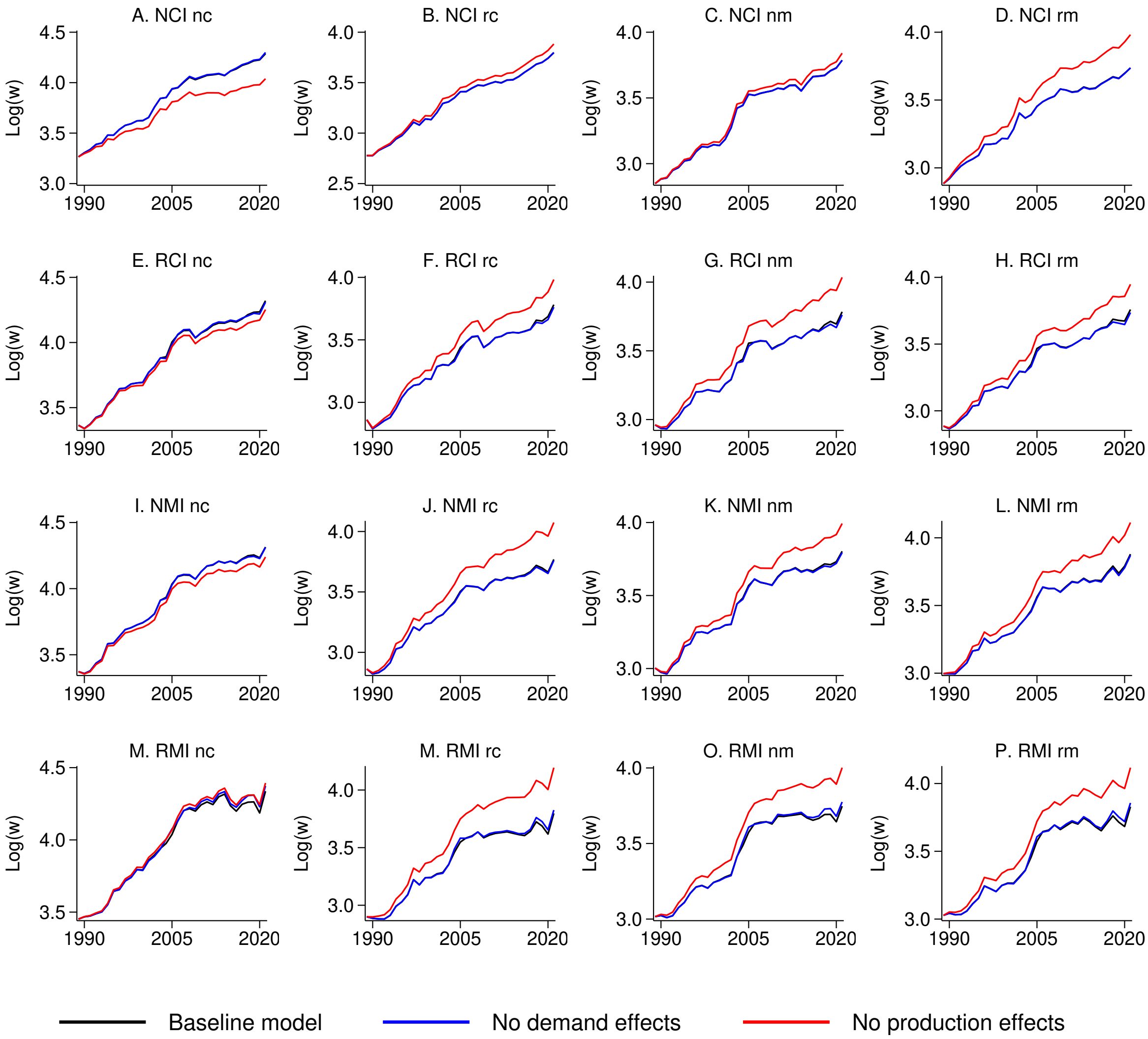

Figure A.21: Wage Counterfactuals Over Time for $\eta = 0$

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.

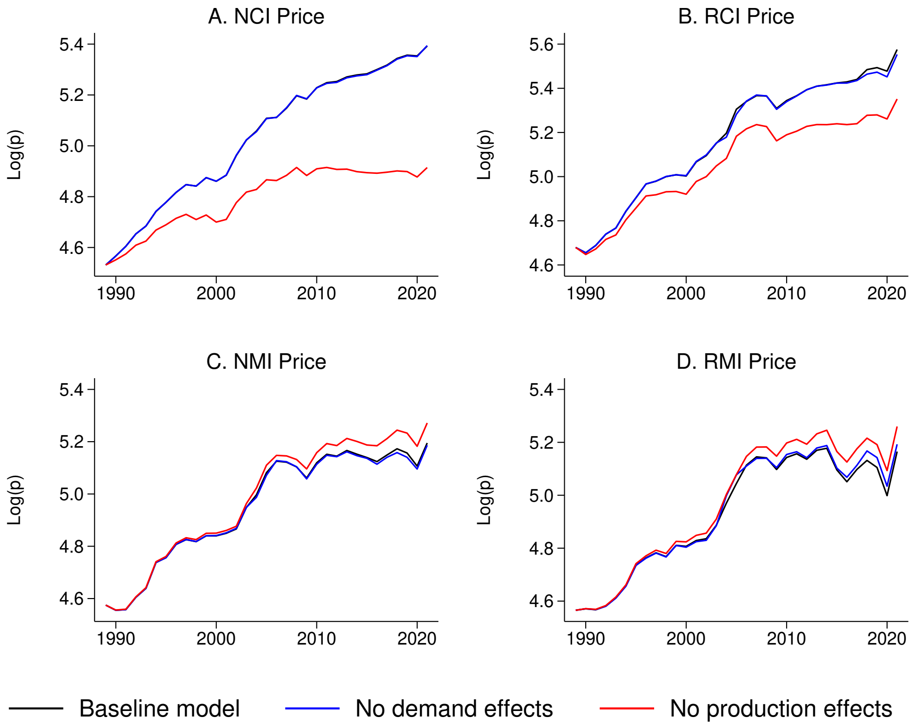

Figure A.22: Price Counterfactuals Over Time for $\eta = 0$

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.

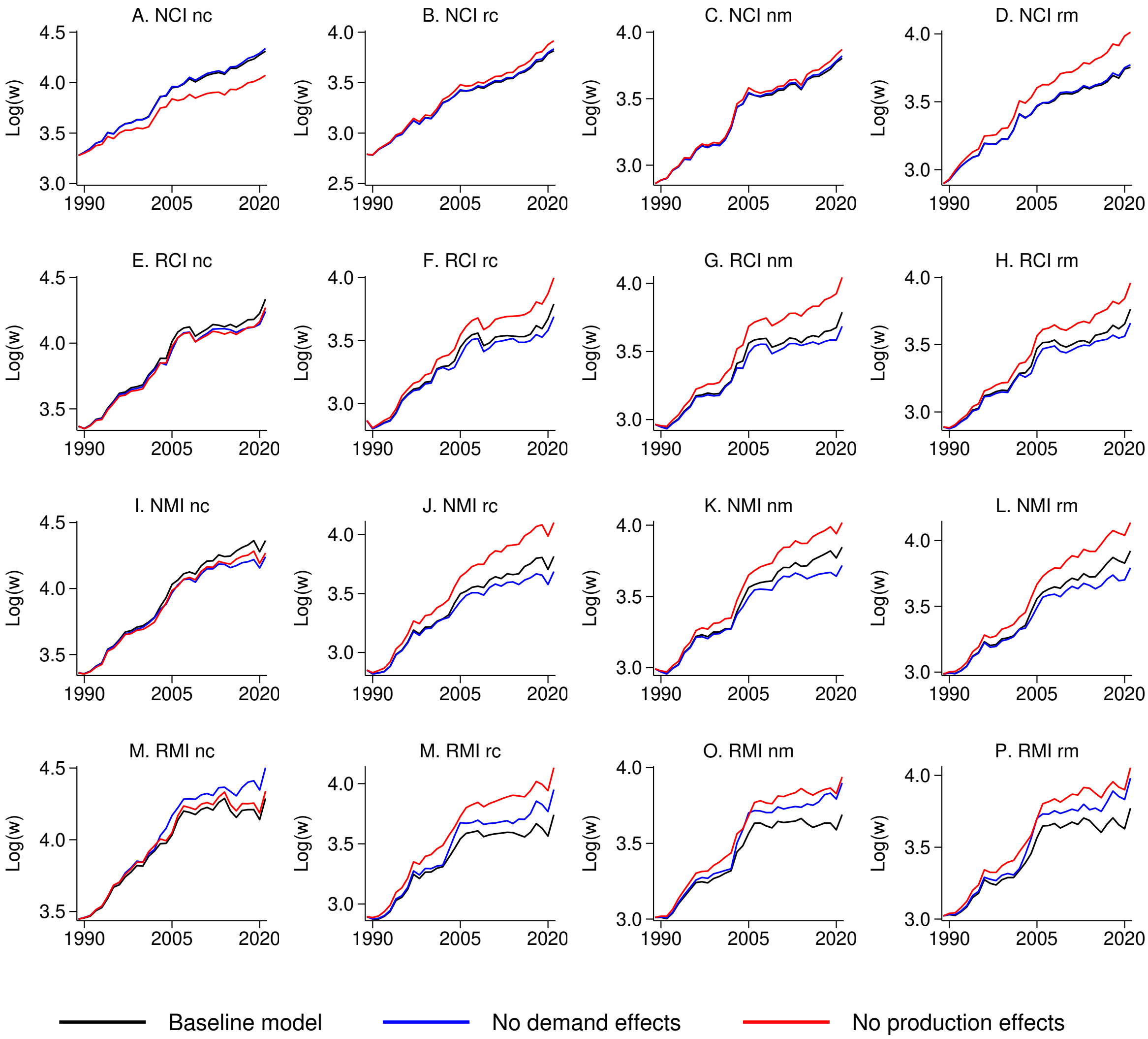

Figure A.23: Wage Counterfactuals Over Time for $\eta = 1.5$

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.

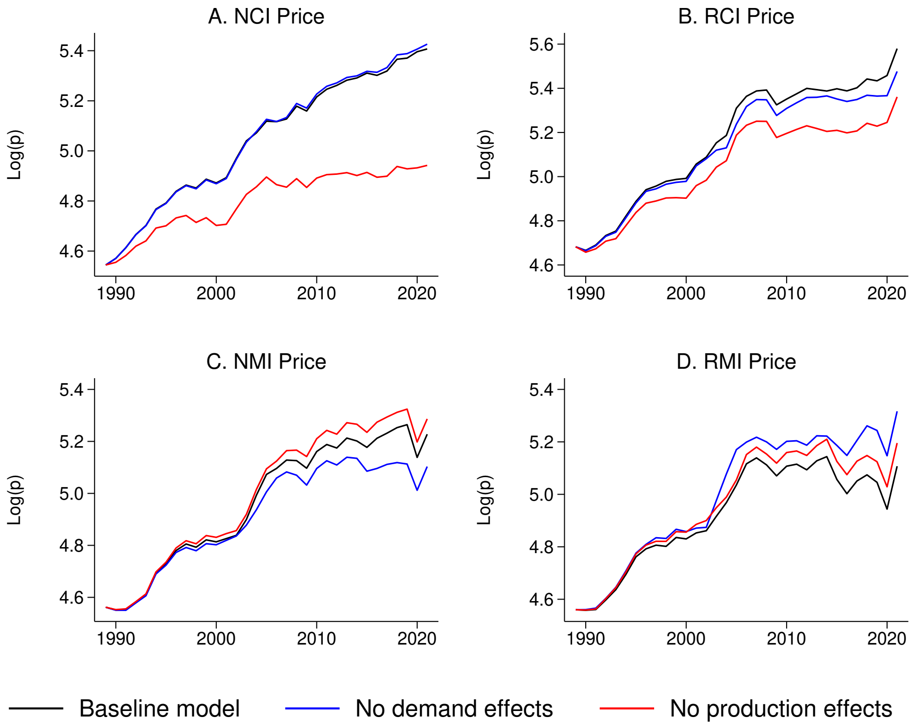

Figure A.24: Price Counterfactuals Over Time for $\eta = 1.5$

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.

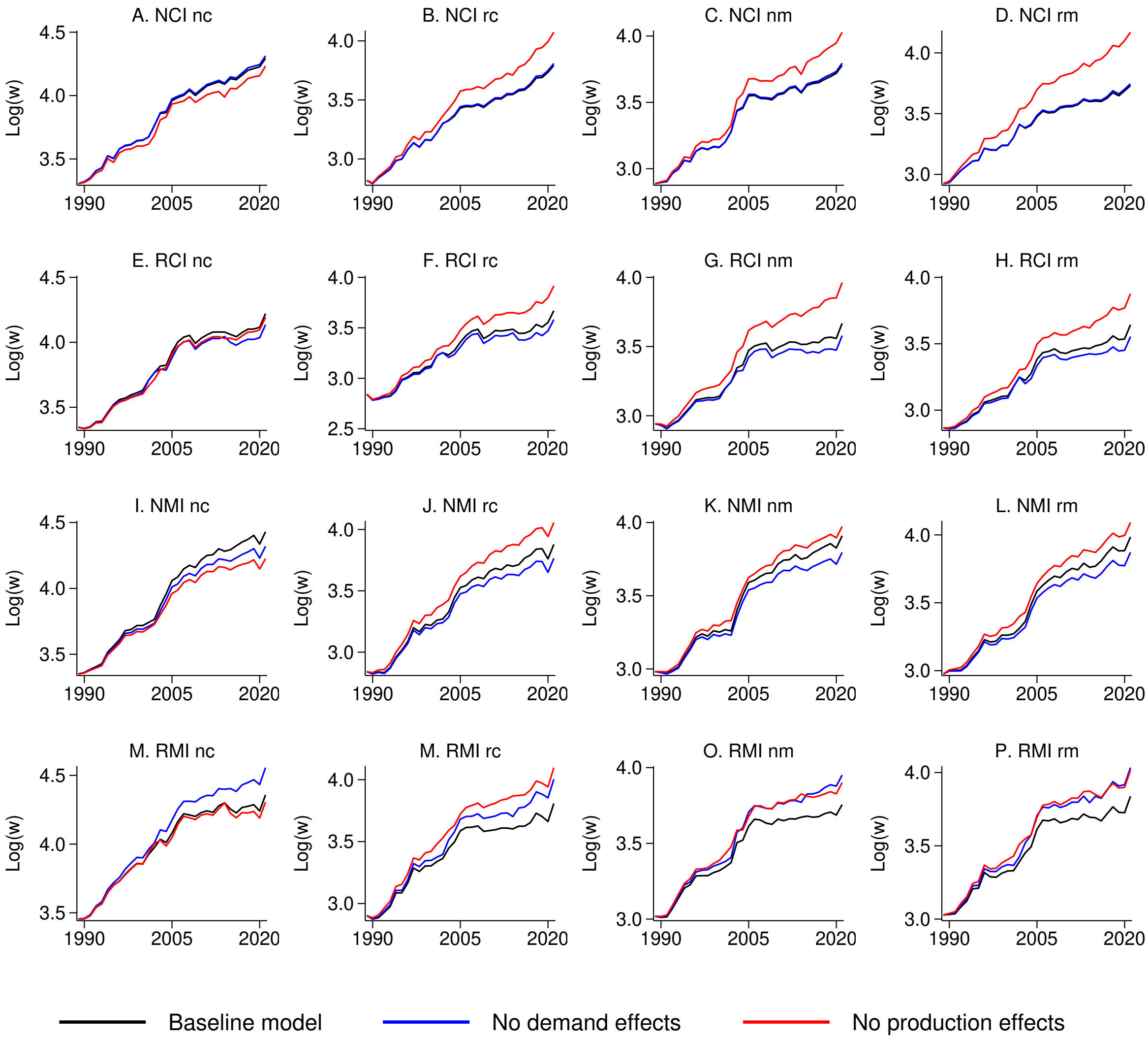

Figure A.25: Wage Counterfactuals Over Time for $\eta = 4.5$

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.

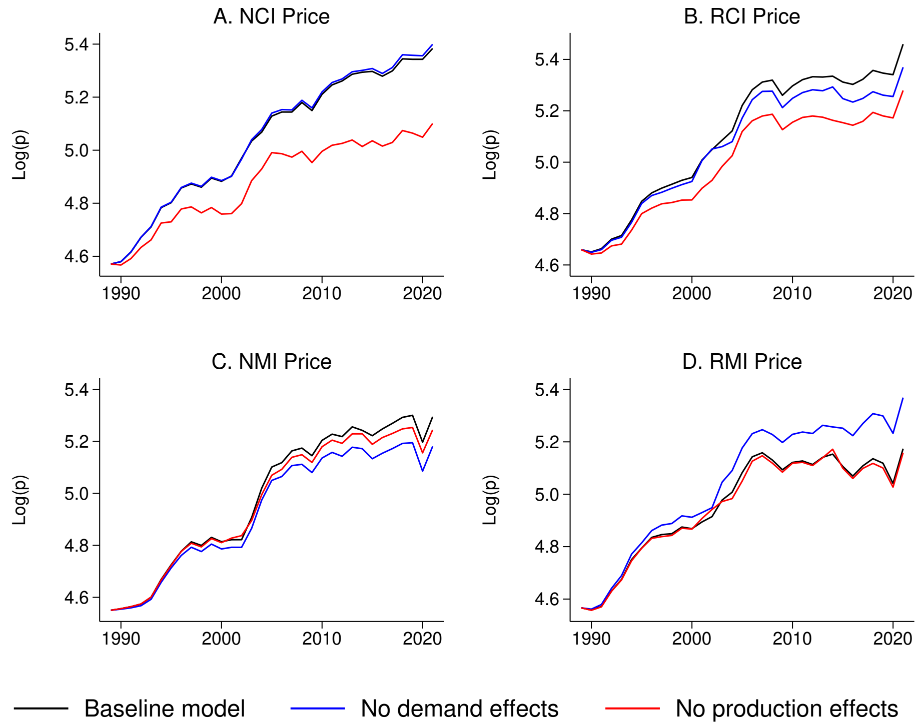

Figure A.26: Price Counterfactuals Over Time for $\eta = 4.5$

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.

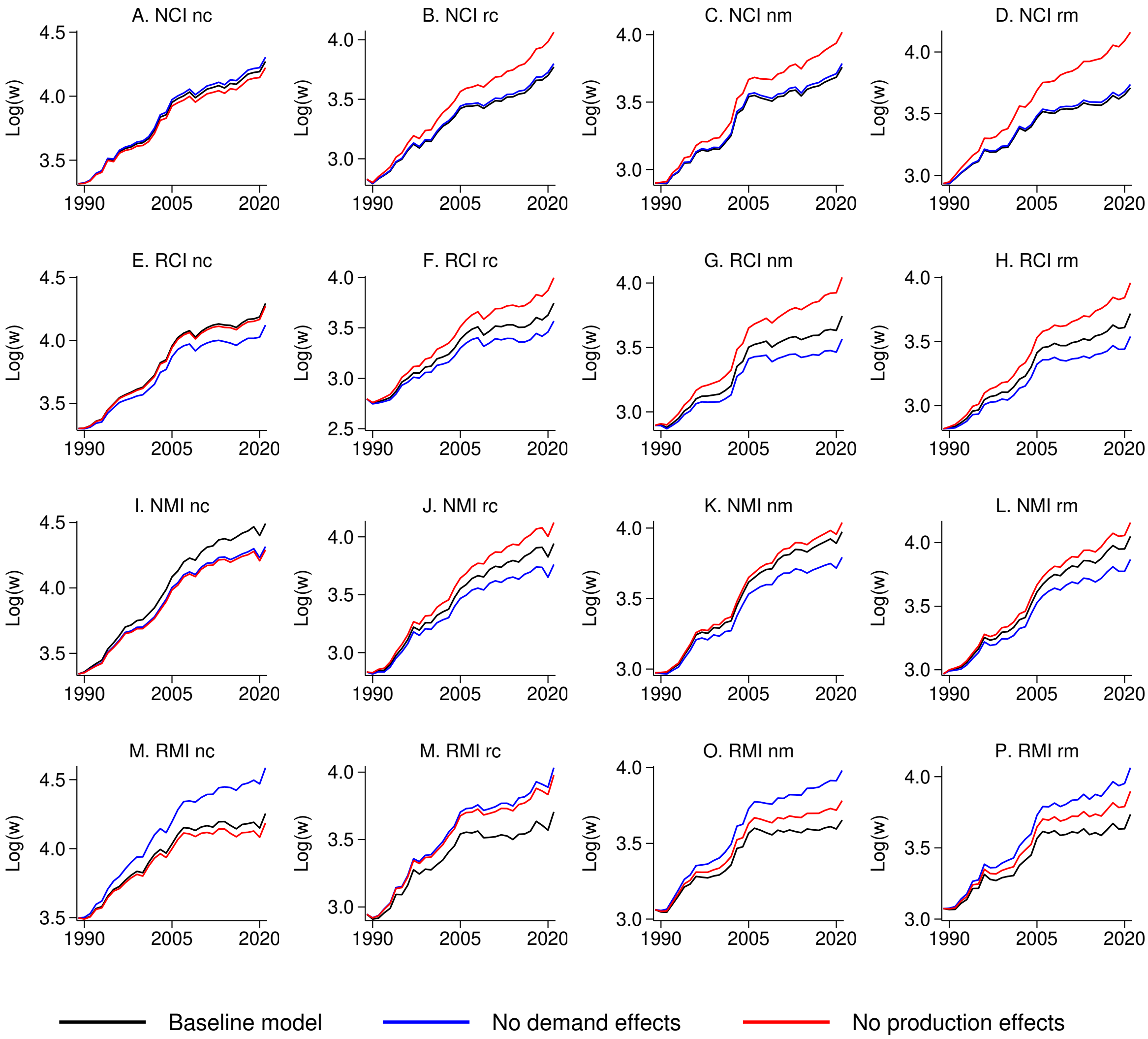

Figure A.27: Wage Counterfactuals Over Time With no Subsistence Levels

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.

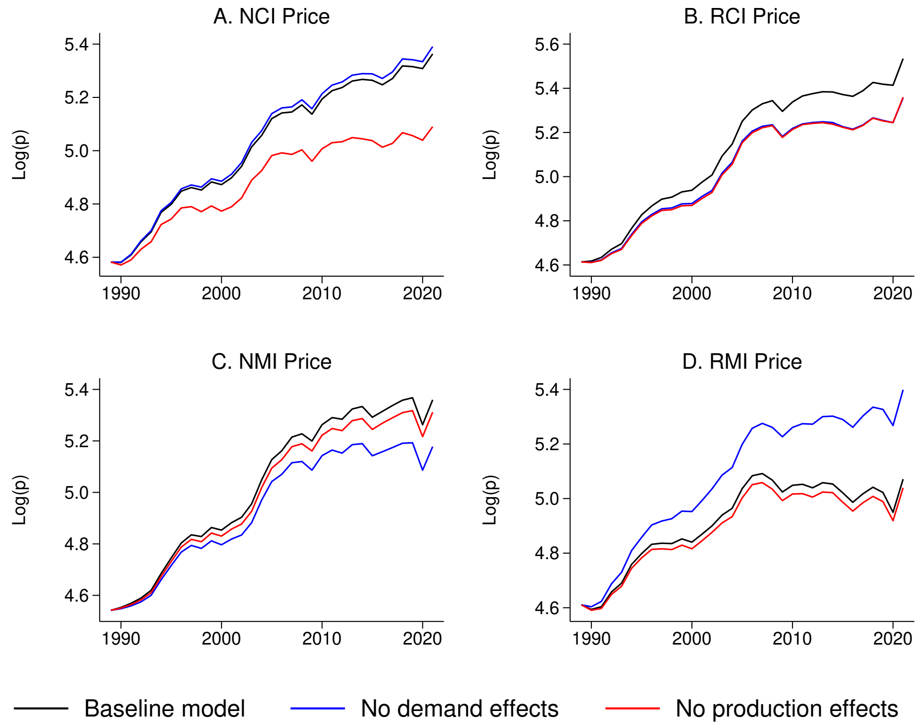

Figure A.28: Price Counterfactuals Over Time With no Subsistence Levels

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.

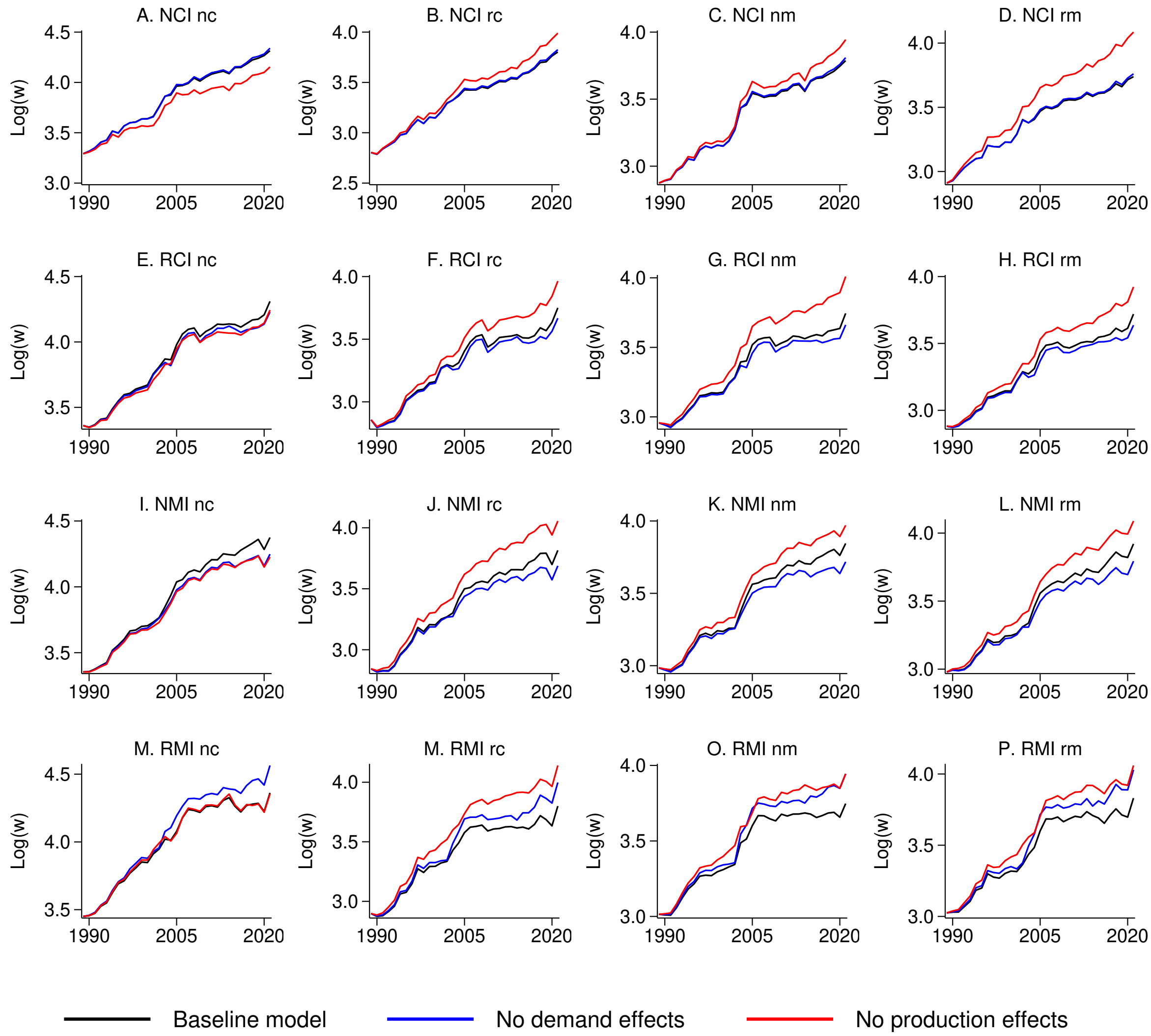

Figure A.29: Wage Counterfactuals Over Time with Constant Household Distribution

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.

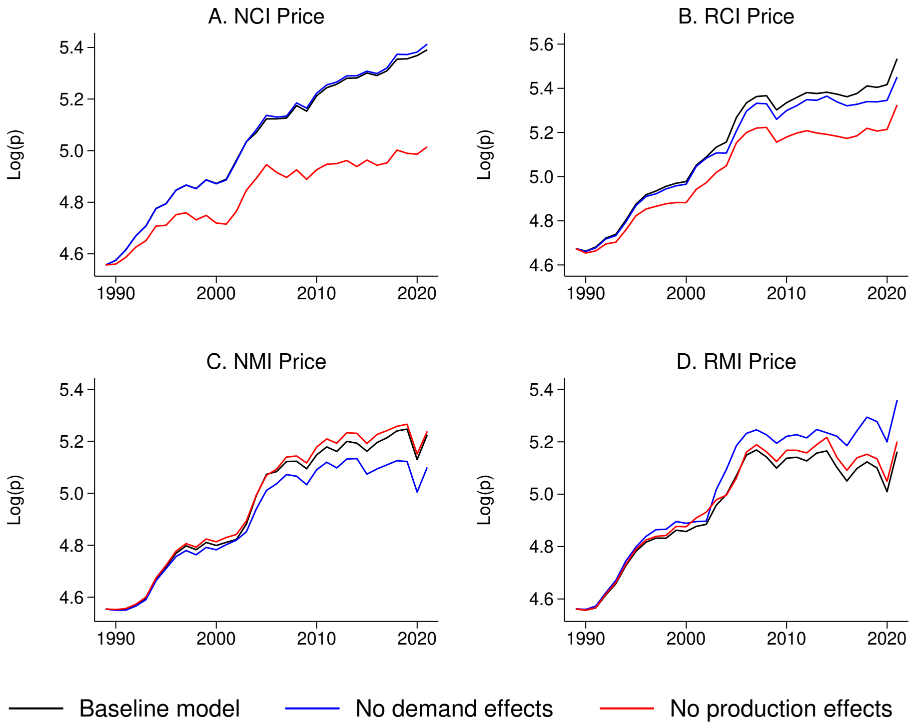

Figure A.30: Price Counterfactuals Over Time with Constant Household Distribution

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.

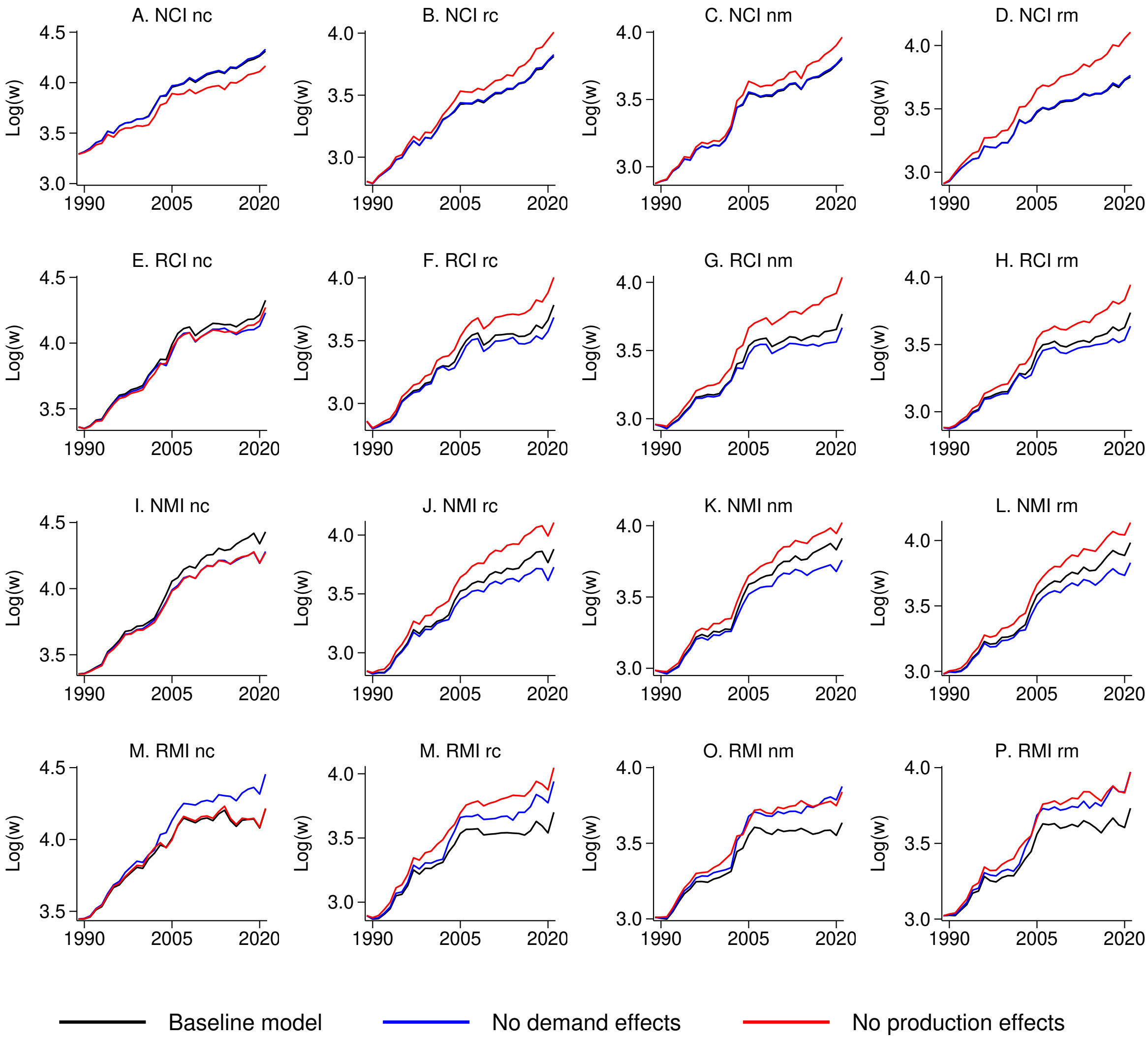

Figure A.31: Wage Counterfactuals Over Time with Adjusted labour Allocations Based on Labour Distribution

Note: Labour distribution is kept constant at the level of 1989 for all years by scaling labour with sector specific labour adjustment rate. 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.

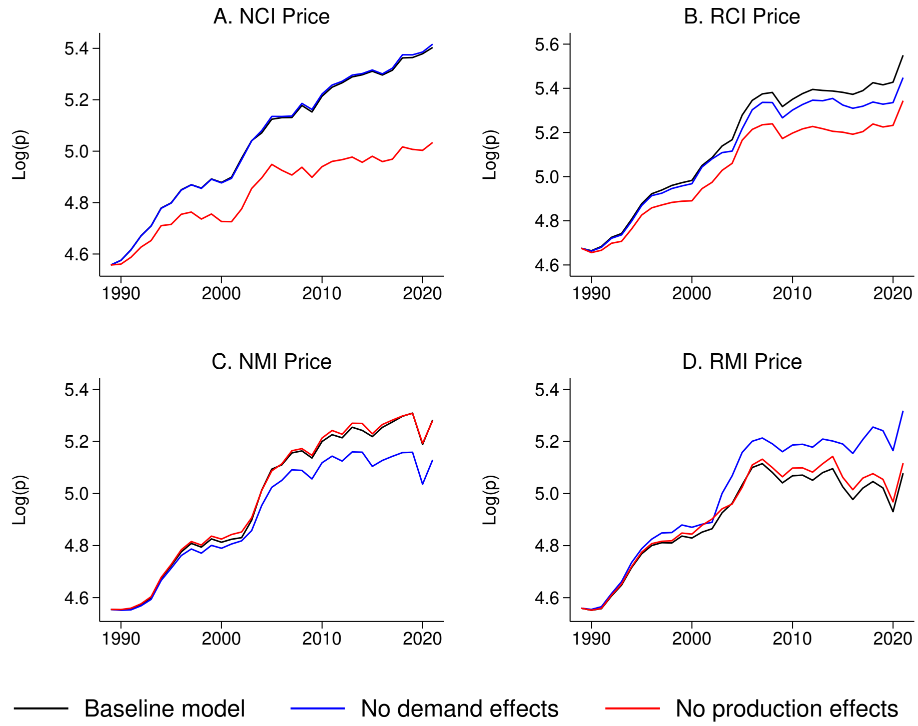

Figure A.32: Price Counterfactuals Over Time with Adjusted labour Allocations Based on Labour Distribution

Note: Labour distribution is kept constant at the level of 1989 for all years by scaling labour with sector specific labour adjustment rate. 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.

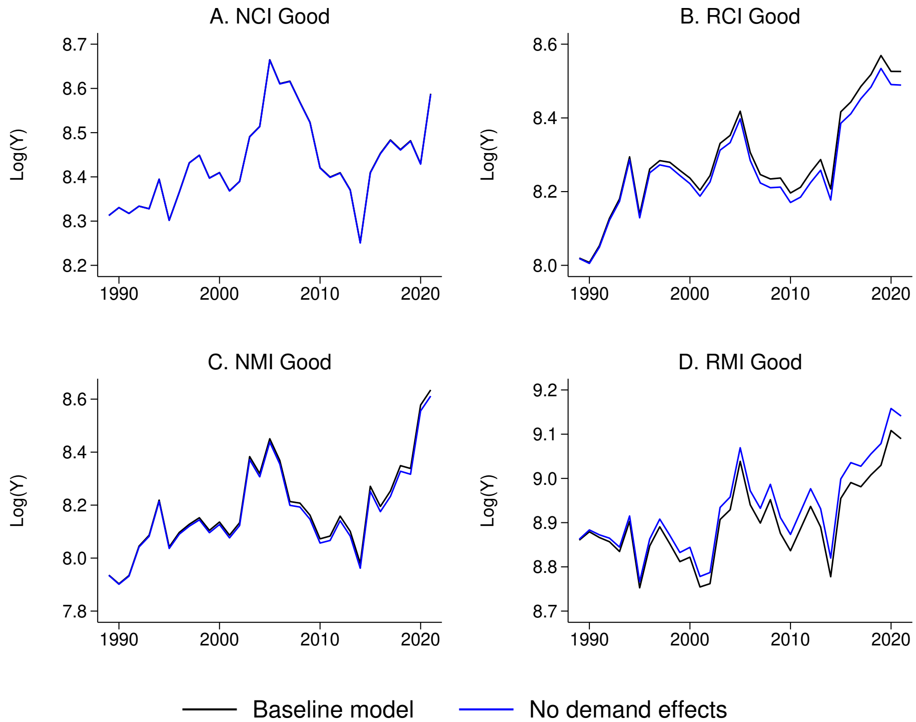

Figure A.33: Output Counterfactuals Over Time with Adjusted labour Allocations Based on Labour Distribution

Note: Labour distribution is kept constant at the level of 1989 for all years by scaling labour with sector specific labour adjustment rate. 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.

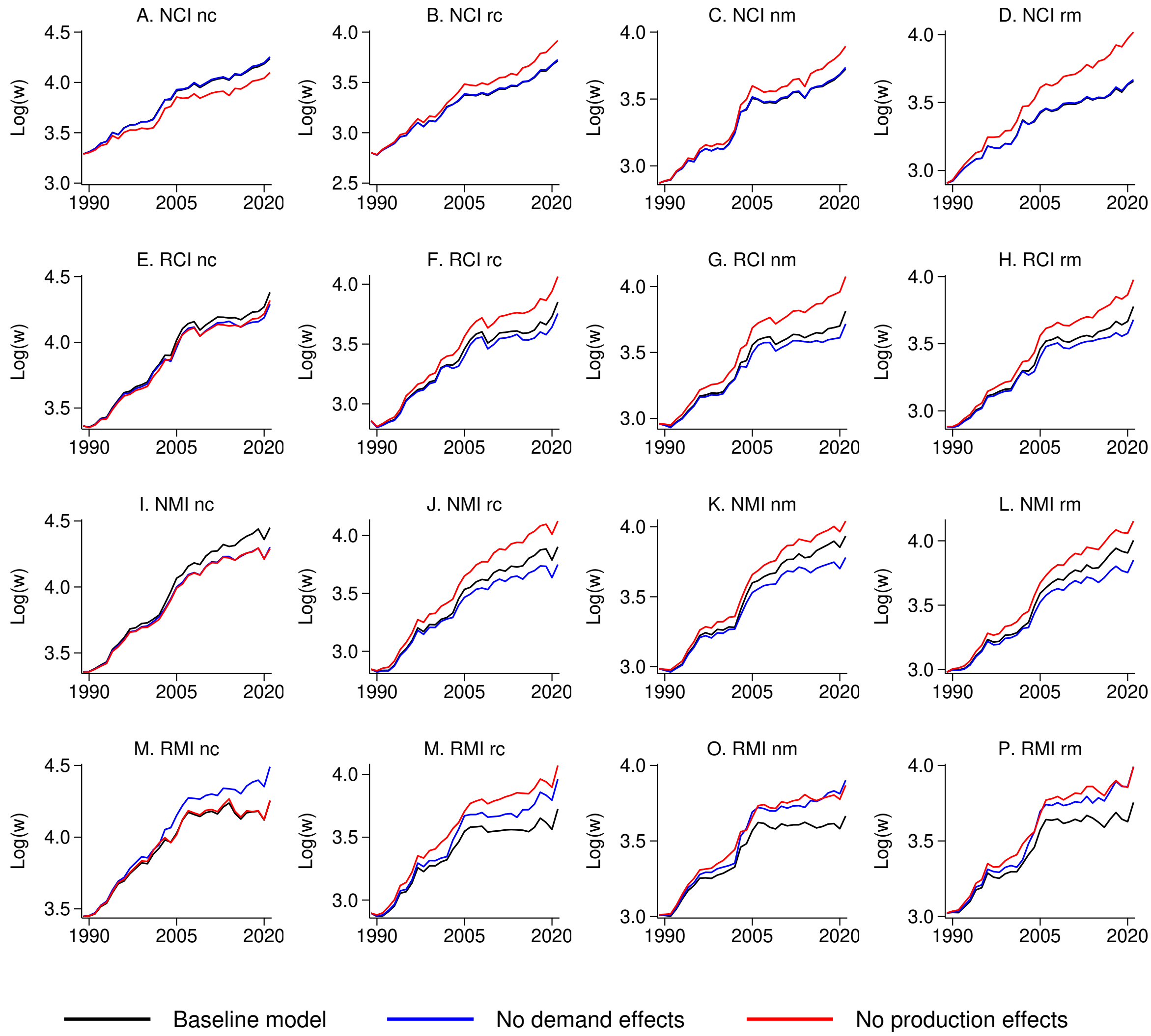

Figure A.34: Wage Counterfactuals Over Time with Adjusted labour Allocations Based on Output Quantities

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.

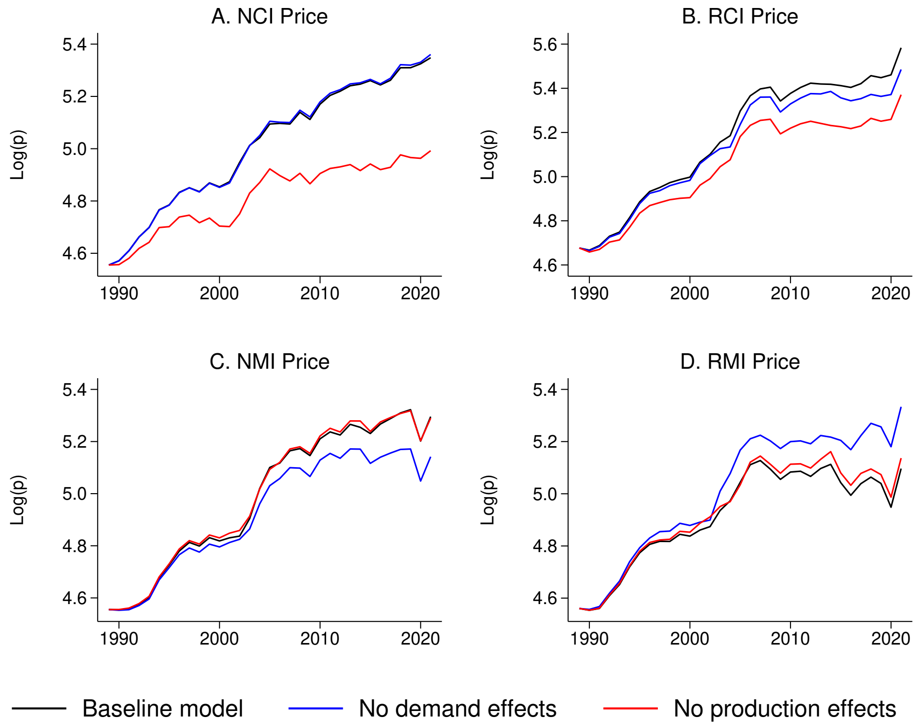

Figure A.35: Price Counterfactuals Over Time with Adjusted labour Allocations Based on Output Quantities

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.

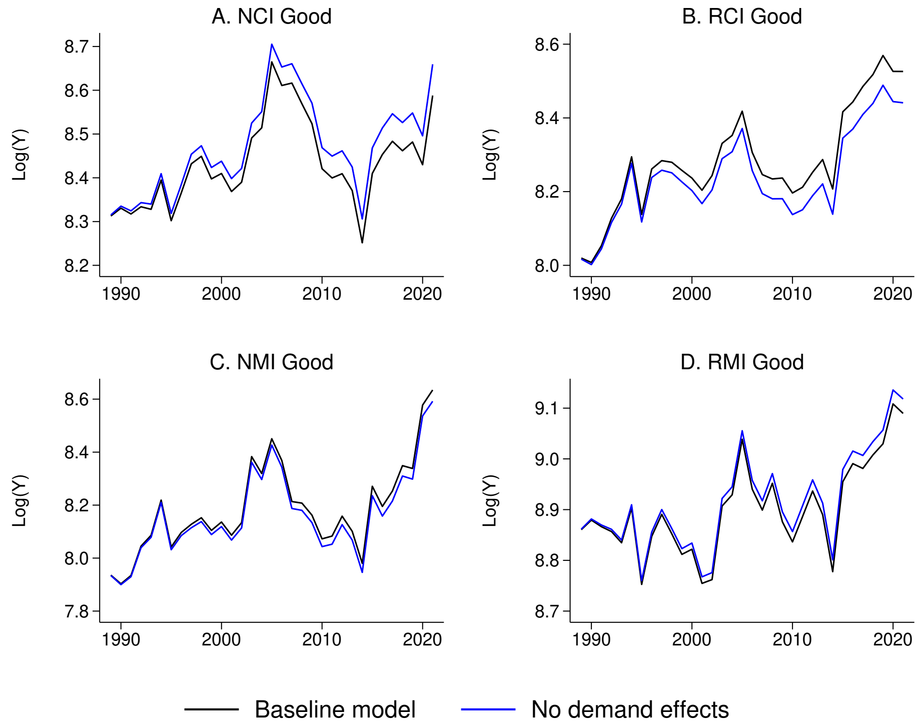

Figure A.36: Output Counterfactuals Over Time with Adjusted labour Allocations Based on Output Quantities

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.

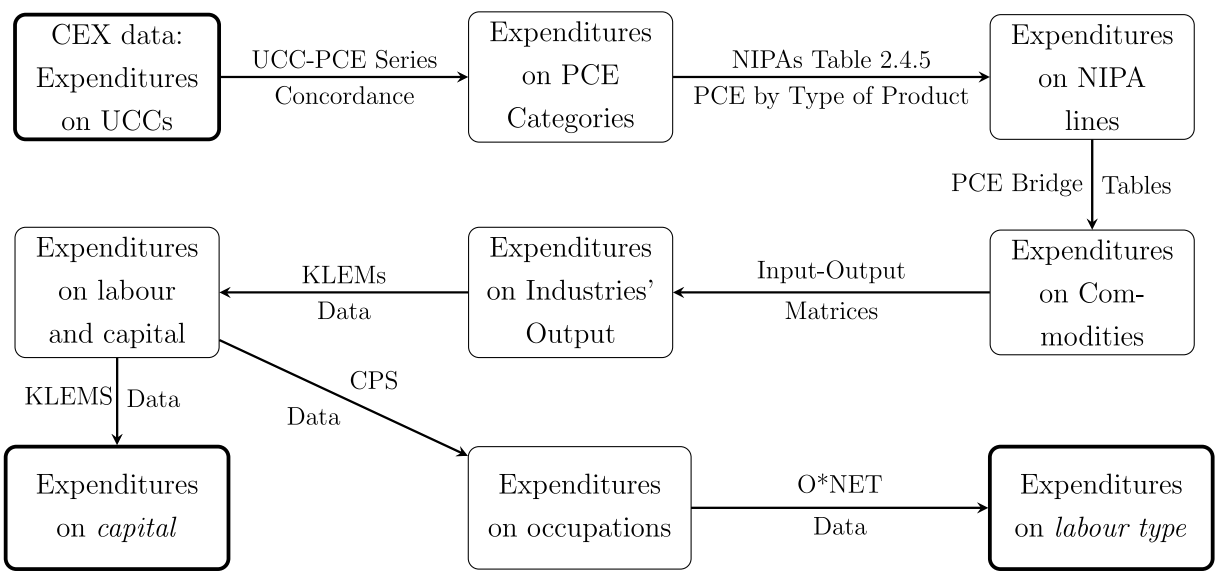

Figure B.1: Data preparation steps

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.[30] 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.[31] 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".[32] In 2004, BLS started providing an imputed income variable – SALARYX.[33] 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.[34] 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[35].

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

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

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

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

[34] 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.

[35] 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)
Household 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)
Respondent 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.

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.[36] 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.[37] 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.[38] 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

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

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

[38] 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.[39] 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.[40] 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

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

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

using Current Population Survey (CPS) data, provided by the BLS.[41] 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

[41]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.

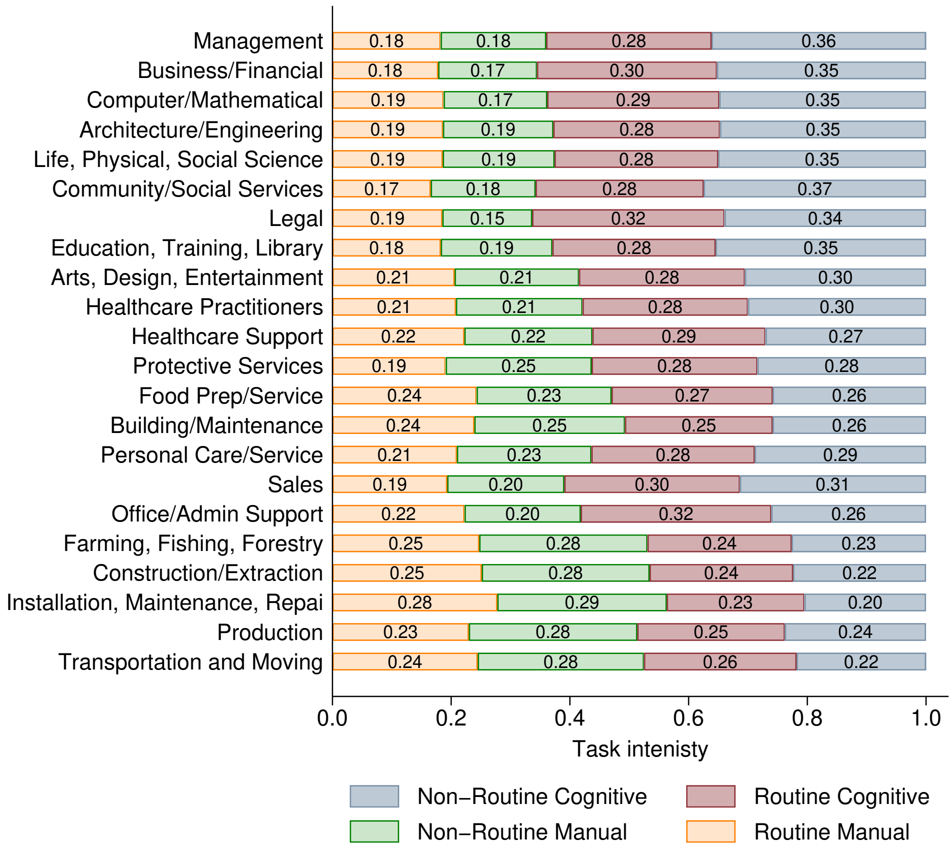

Figure B.2: Average Task Intensities by Occupation Group

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

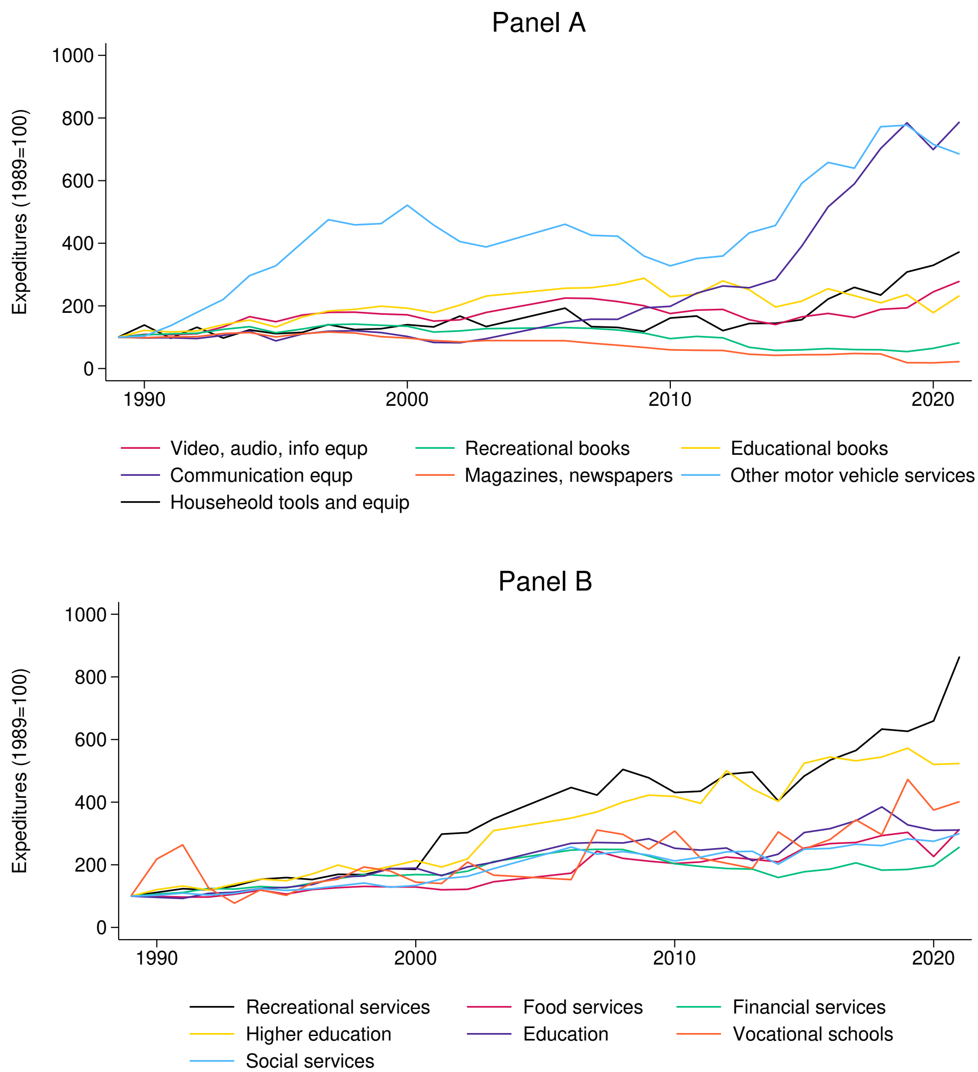

Figure B.3: Non-Routine Cognitive Intensive (NCI) NIPA lines

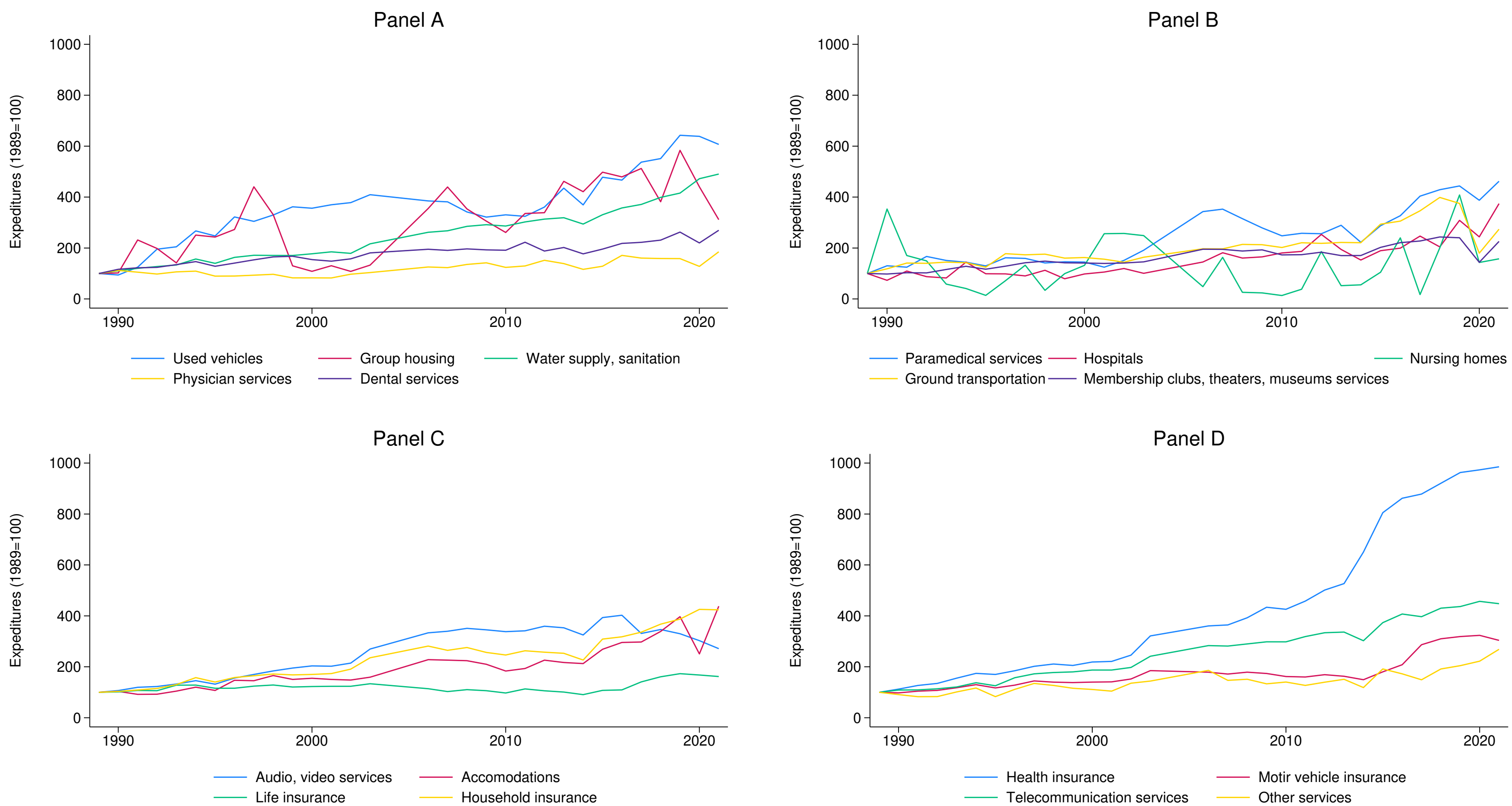

Figure B.4: Routine Cognitive Intensive (RCI) NIPA lines

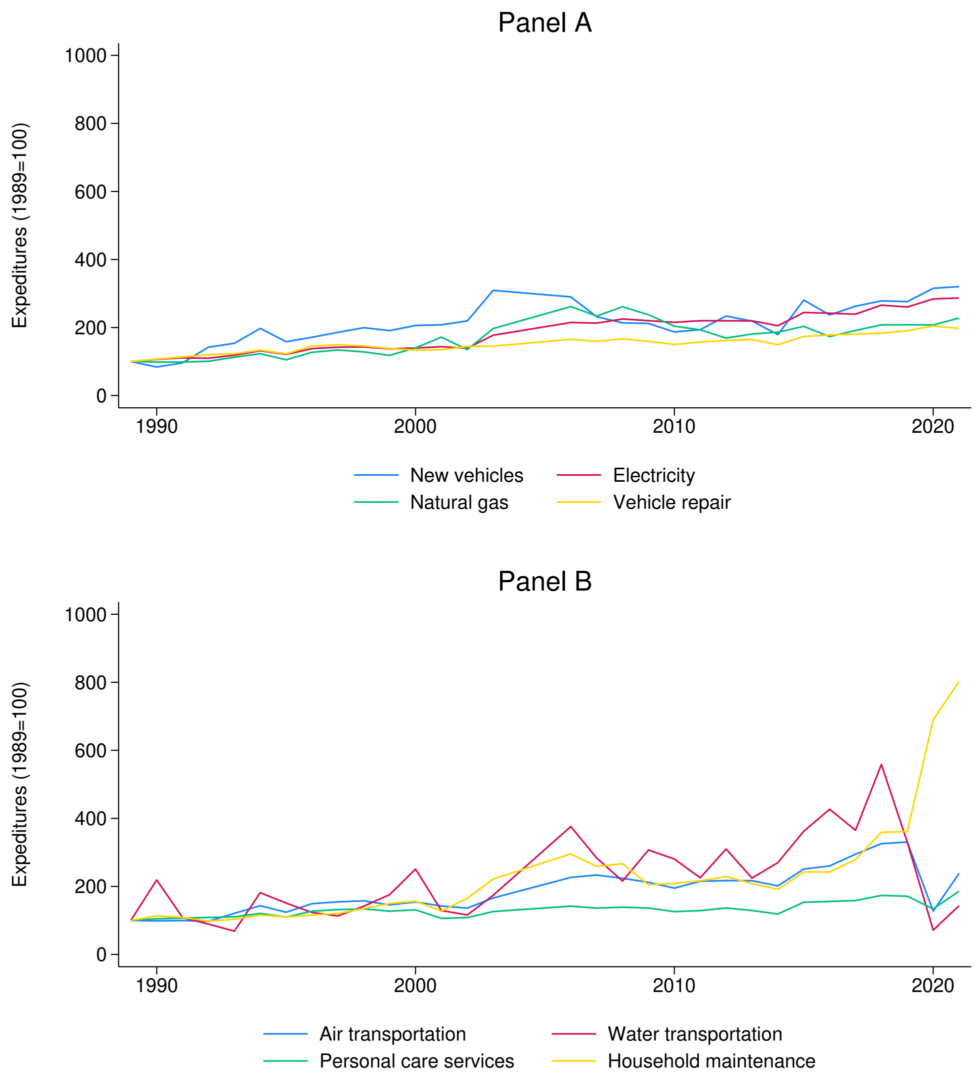

Figure B.5: Non-Routine Manual Intensive (NMI) NIPA lines

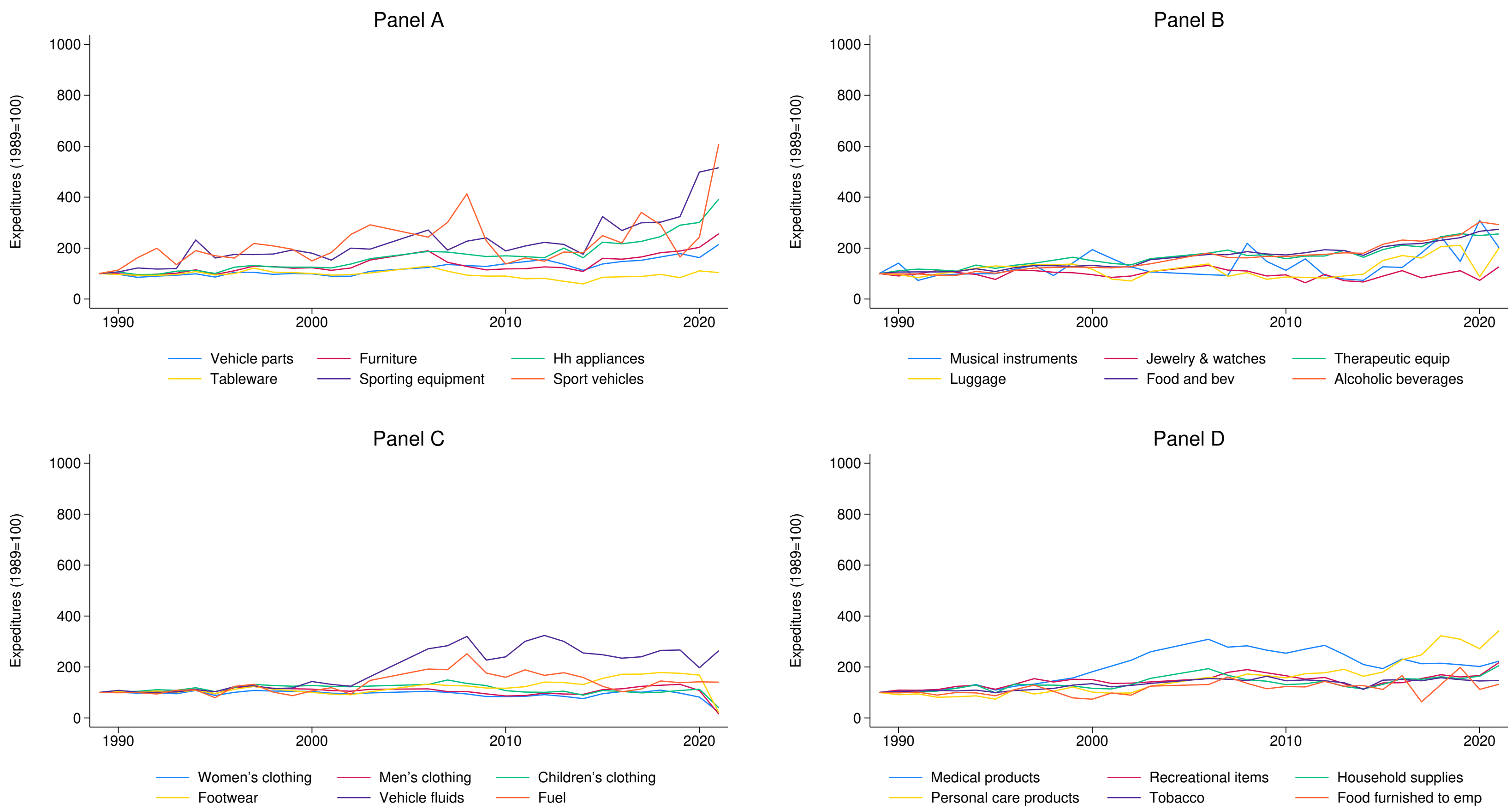

Figure B.6: Routine Manual Intensive (RMI) NIPA lines

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.

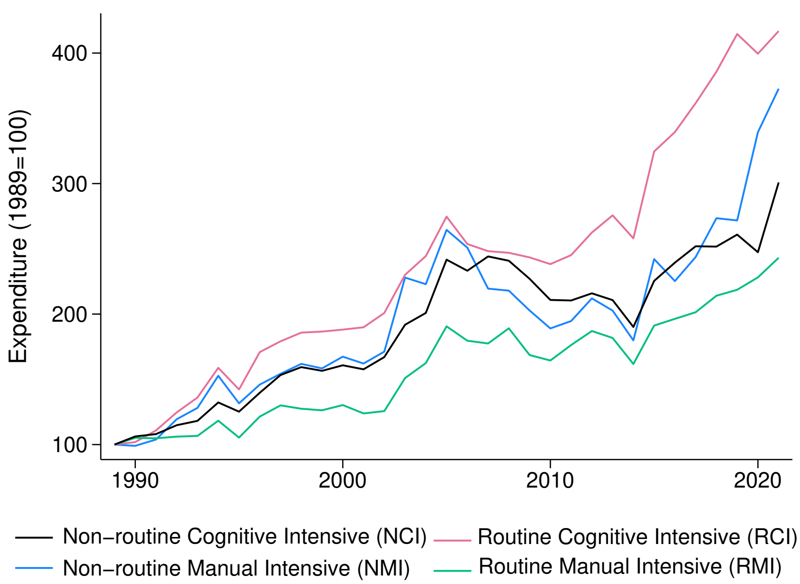

Figure B.7: Expenditures by Good Type Over Time

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.

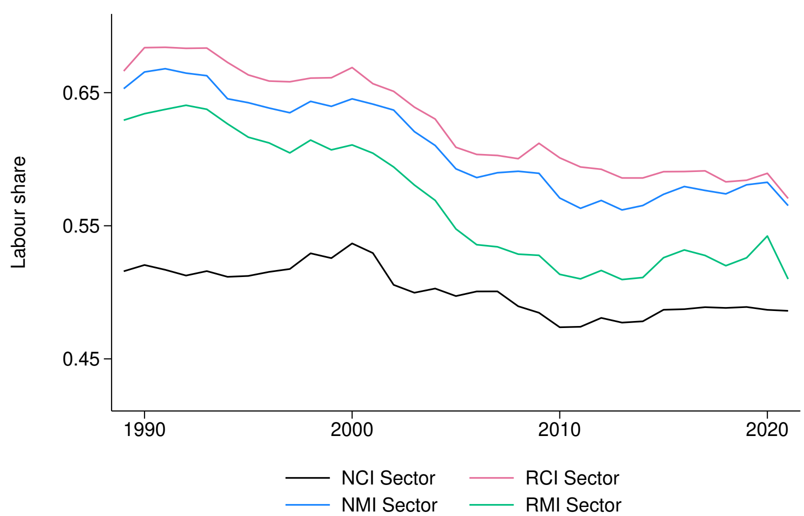

Figure B.8: Labour Share by Sector Over Time

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. [42] 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.

[42] 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.

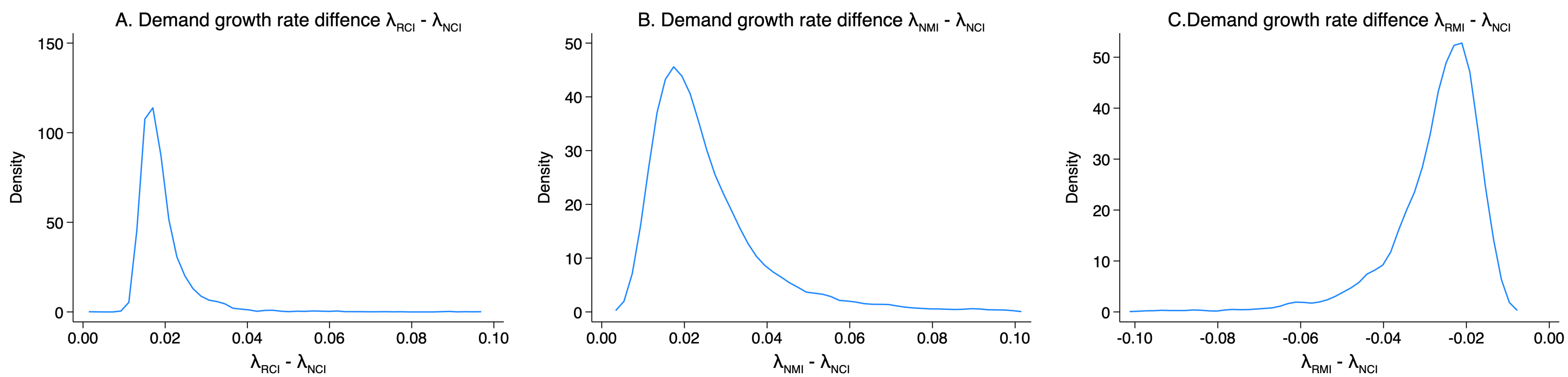

Figure C.1: Distribution of Differences in Demand Growth Rates from Monte-Carlo Simulations

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.