Income Inequality and Aggregate Demand

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Abstract

This paper investigates the relationship between income inequality and aggregate demand. It is shown empirically, that increases in income inequality are associated with decreased aggregate consumption. The analysis reveals a systematic difference in the relationship between income inequality and consumption expenditure across consumption categories In a theoretical analysis, the effect of an exogenous skill-biased technological change on equilibrium prices and expenditure shares is derived for the case of homothetic CES preferences and the case of non-homothetic CES preferences. In both cases, equilibrium prices and expenditure shares are affected via a supply-side channel. In the case of non-homothetic CES preferences, they are also affected via a demand-side channel, due to changes in income inequality. The comparison of model predictions under homothetic and non-homothetic preferences results in estimation equations that allow testing for non-homotheticity in consumption data. Empirical results indicate that preferences are indeed non-homothetic. Furthermore, the non-homothetic CES preferences are well suited to explain the distinct pattern observed between consumption categories and income inequality. In addition, a quantification of the novel demand-side channel is done to determine its direction and size. The results suggest, that the demand-side channel ameliorates exogenous changes in income inequality and is non-trivial in size.

1 Introduction

It is a well-documented fact that income inequality has increased over the last decades, as discussed for example by Piketty and Goldhammer (2014) and Saez and Zucman (2020). The 2007-2008 financial crisis and its broader economic ramifications made income inequality a topic of public interest. This was manifested for example in the Occupy Wall Street movement in 2011, which forced politicians to confront the issue. In a speech given at the White House, Krueger (2012), then Chairman of the President's Council of Economic Advisers, argued that a redistribution of income could boost aggregate demand. He invokes the idea of a dwindling Middle Class harming aggregate demand and sees a possible "latent pressure" on aggregate demand, caused by income inequality. The notion that income inequality affects aggregate demand is not new. There is a large literature analyzing how income inequality relates to economic growth, mostly finding a negative relationship (see, for example, Persson and Tabellini (1994) Murphy *et al.* (1989), and Berg *et al.* (2012)). The mechanism put forward by economic theory is that variations in consumption patterns across income groups can influence the overall level of demand in the economy and through it economic growth.

This paper suggests an additional channel through which income inequality affects aggregate demand, namely by influencing its composition. In a first step, the relationship between income inequality and aggregate demand is investigated empirically, using US state-level expenditure data from 1997-2018. The results indicate, that income inequality and aggregated personal consumption expenditures are negatively correlated. The US data covers not only personal consumption expenditure aggregates but also reports consumption expenditures at a more disaggregated level. Analyzing the subcategories of consumption expenditures shows that the negative effect between income inequality and aggregate demand is solely driven by demand for services, which in the aggregate even overcompensates a positive effect of income inequality on goods consumption. Both the negative relationship between income inequality and aggregate demand and the distinctive pattern emerging from analyzing demand subcategories is also present in German EVS data from 2003 and

2018. While the former finding confirms the intuition voiced for example by Krueger (2012), the finding of the robust, distinctive pattern in the relationship between income inequality and consumption subcategories is a novel empirical finding.

The empirical results reported in this paper suggest that income inequality affects both the level and the composition of aggregate demand. To gain a better understanding of the mechanism through which inequality affects demand for different consumption subcategories, a theoretical model is formulated. Following the example of Comin *et al.* (2021), a model featuring non-homothetic preferences over two types of goods is developed. The model abstracts from the effect income inequality has on the level of aggregate demand, but it is well suited to illustrate how income inequality changes the composition of aggregate demand. Specifically, it illustrates how the non-homotheticity of preferences opens up a demand-side channel through which income inequality affects aggregate demand, which can have an amplifying or ameliorating effect on income inequality. In addition, and depending on the income elasticity of the consumption categories services, durable, and non-durable goods, the model can explain why an increase in income inequality increases demand for goods but decreases demand for services. Specifically, for the model to explain the empirical finding, the income elasticity of services has to lie between those of durable and non-durable goods. In that case, households with decreasing income consume more non-durable goods and fewer services, whereas households with increasing income consume more durable goods and fewer services, resulting in the pattern observed in the data.

The model suggests that income inequality affects demand composition because income elasticities vary across consumption categories. In the next step, income elasticities of the consumption categories are estimated using US data and the approach proposed by Aguiar and Bils (2015) as well as German EVS data and the approach proposed by Comin *et al.* (2021). This is analogous to estimating the marginal propensity to spend on different consumption categories, which is constant across income groups. In that regard, the estimation approach is distinct from the one used in previous literature, which has focused on estimating marginal propensities to consume at different levels of income. Irrespective of the data used and the empirical strategy employed, the income elasticities are indeed estimated to increase from non-durable goods to services to durable goods. Thus, the estimated income elasticities are such that the model can explain the decreased demand for services and the increase in demand for goods, both durable and non-durable.

In the final step, the novel demand-side channel emerging from the model is quantified in an attempt to demonstrate its importance. To that end, it is analyzed if changes in aggregate consumption composition driven by income inequality reinforce or dampen wage inequality, which is measured by the skill premium. The results indicate that income inequality-driven changes in consumption composition ameliorate the original increase in income inequality, by increasing demand for goods produced in industries paying relatively low skill premia. The back-of-the-envelope calculation indicates that income inequality decreased by about 0.2 percentage points due to the dampening influence of changes in consumption composition for every percentage point increase in income inequality.

There is a large literature investigating how income inequality affects the level of aggregate demand. In their analysis of marginal propensities to consume, Fisher *et al.* (2020) find that marginal propensities to consume differ systematically across wealth and income quintiles. They conclude that it is crucial to account for income and wealth distributions to calculate the effect of, for example, fiscal stimulus, and increases in income per capita in general, on aggregate expenditure. In a series of papers, Mian *et al.* (2020), Mian *et al.* (2021a), and Mian *et al.* (2021b) use non-homothetic preference to build models explaining how income inequality affects aggregate economic outcomes such as household borrowing, interest rates, and wealth inequality. The models and accompanying empirical findings highlight how high-income households, with greater purchasing power, allocate a larger share of their income to investments and savings, thereby dampening aggregate demand. In a similar vein, Corneo (2018) develops a simple microeconomic model to analyze the effect of increasing income inequality on aggregate demand. Other papers analyzing the inequality consumption nexus theoretically are Auclert and Rognlie (2017) and Bilbiie *et al.* (2022). Only a few papers are trying to estimate the effect of income inequality on aggregate demand at the macro level. Stockhammer and Wildauer (2016) fail to find a significant relationship in a sample of OECD countries. Crespo Cuaresma *et al.* (2018) regress average propensity to consume on income inequality and find, if anything, a positive relationship which they interpret as evidence against income inequality negatively affecting aggregate demand. In contrast, Brown (2004) does find a significantly negative relationship between consumption expenditures and income inequality. The estimates are derived using only US data and time series analysis.

There is ample and constantly increasing evidence for non-homotheticities in consumer preferences. For example, Straub (2019) finds an income elasticity of 0.7 over his preferred averaging period of nine years. The estimated income elasticity is well below one, the value to be expected in the case of homothetic preferences. The income elasticity estimate in this paper is slightly lower at 0.5, but given the shorter time horizon, it is even higher than what Straub (2019) finds for short time periods. Aguiar and Bils (2015) analyze to which extent consumption inequality mirrors income inequality and conclude that the relationship is quite strong. Their estimation approach relies on relative expenditures on necessities and luxuries, implying that they base their analysis on non-homothetic preferences. Comin *et al.* (2021) introduce a non-homothetic CES utility function and demonstrate how its parameters can be estimated. In a direct comparison of the same non-homothetic CES utility to standard homothetic CES utility, this paper demonstrates how to test for non-homotheticity empirically. The results indicate that consumer preferences are indeed non-homothetic.

This paper uses non-homothetic preferences to illustrate how income inequality affects aggregate demand. Intuitively, high-income households allocate a larger share of their income to luxury goods whereas lower-income households, facing limited resources, often prioritize necessities and essential goods. Changes in income inequality thus result in shifts in the composition of goods and services demanded, thereby impacting specific industries or sectors. There is a pertaining literature analyzing how changes in aggregate demand can impact other macroeconomic aggregates. These shifts can have broader economic ramifications, including the demand for differently skilled labor inputs. In the structural change literature, these aspects play an important role (see for example Boppart (2014), Cravino and Sotelo (2019), Comin *et al.* (2020) Comin *et al.* (2021), and Buera *et al.* (2022)). Furthermore, these studies often find that structural change is associated with changes in income inequality and in particular wage polarization (see Autor *et al.* (2005a), Autor *et al.* (2005b), Autor *et al.* (2006), and Bárány and Siegel (2018), all using US data). Goos and Manning (2007) show the same pattern for the UK. Spitz-Oener (2006) and Dustmann *et al.* (2009) show that this also holds for Germany, a country previously singled out to have the least wage polarization. The pertaining literature and shortcomings thereof are thoroughly discussed in Acemoglu and Autor (2010).

The literature review suggests that income inequality, aggregate demand, and consumption patterns are intricately linked factors that shape economic dynamics and outcomes. This paper demonstrates that a comprehensive understanding of the relationship between these elements requires accounting for the role of non-homothetic preferences – the idea that individuals' consumption patterns change with variations in their income levels. In the case of homothetic preferences, changes in income inequality do not affect aggregate demand. Non-homothetic preferences introduce a crucial dimension to the study of income inequality and its impact on aggregate demand, as they affect not only the magnitude but also the composition of consumption across income groups. This in turn affects income inequality through the demand-side channel. The paper is structured as follows. In Section 2, the relationship between income inequality and aggregate demand as well as subcategories of consumption is estimated empirically. Section 3 introduces the model featuring both homothetic and non-homothetic preferences. Subsequently, estimated income elasticities of different consumption subcategories are presented in Section 4. Finally, the demand-side channel is quantified in Section 5. Section 6 concludes.

2 Estimating Aggregate Demand

The empirical analysis in this section examines the correlation between income inequality and aggregate demand, as well as various subcategories of consumption. Throughout the paper, empirical analysis is conducted using data from the US and Germany. Both are briefly described in the following. Subsequently, the empirical identification strategy is discussed and estimation results, which are derived from regressions using the two distinct data sets, are presented.

2.1 Data

To analyze the relationship between income inequality and aggregate demand, US state-level data from 1997-2018 provided by the Bureau of Economic Analysis (BEA) is combined with data from the World Inequality Database (WID).[1] The BEA provides information on personal consumption expenditures, both in absolute and in per capita terms. Total personal consumption expenditures are further broken down into 15 subcategories as classified in the National Income and Product Accounts (NIPA).[2] Additionally, data on income and income per capita can be obtained from the BEA. The focus throughout the analysis will be on per capita terms. As an inequality measure, the share of income going to the Top 10% of the income distribution is used. The data available at the WID is prepared and continually updated by Mark Frank, see Frank (2009). Importantly, it is calculated at the state level for each year, such that the income inequality measures varies across states and time.

The German data comes from the EVS, which is a triennial, repeated cross-sectional household-level survey conducted by the German Statistisches Bundesamt. It reports detailed consumption expenditures as well as socio-demographic information for roughly 40,000 households in each wave. For the analysis in this study, the 2003 and 2018 waves are used. The survey reports the Bundesland of residence for each household, as well as the quarter in which the data was collected. With that information, it is possible to construct a Bundesland-level panel by aggregating the household-level information at the Bundesland-Quarter level. This results in information on each Bundesland for a total of 8

[1] The former data can be found on the website of the BEA (for a short link see `https://t.ly/BOzPa`), the latter on the website of the WID: `https://wid.world/country/usa/`.

[2] These categories are Services (further broken down into Food, Housing, Health, Insurance, Recreation, Transports, Other), Durable Goods (further broken down into Furnishing, Recreation, Vehicles and Other), and Non-durable Goods (broken down into Clothing, Food, Gasoline and Other).

quarters in 2003 and 2018, making panel estimation at the Bundesland-level possible.

2.2 Identification

The goal is to identify the effect income inequality has on personal consumption expenditure and its subcategories. With data available at the state level, state-fixed effects can be included in the regression. This is a first step in the direction of identification, as state-fixed effects act as a catch-all for omitted variables that are constant over time at the state level. Likewise, time-fixed effects are included to account for time variation which is constant across states, such as macroeconomic shocks.

The baseline estimation regresses consumption per capita measures on a variable measuring inequality, income per capita, state- and time-fixed effects, and an error term. Specifically, the estimation equation is given by

$$log(PCE_{s,t}) = \alpha + \beta_1 \cdot Top10\%_{s,t} + \beta_2 \cdot log(Income_{s,t}) + FE_s + FE_t + \varepsilon_{s,t}, \qquad (1)$$

where subscript s refers to state and subscript t refers to time, measured in years.

As dependent variable, aggregated personal consumption expenditure at the state level is used. In addition, subcategories of consumption, such as services and durable and non-durable goods, again aggregated at the state level, are used as dependent variables. The main explanatory variable is $Top10\%$, which measures the share of total income going to the Top 10% of the income distribution. Its effect on consumption expenditures is measured by the coefficient β_1. The variable $Top10\%$ is defined on the range $[0; 100]$. If the share of income going to the Top 10% increases by one percentage point, consumption is estimated to increase by $\hat{\beta_1}\%$.

For the estimation to yield any results, both the outcome variable and the inequality measure have to vary across states and time, such that the variation is picked up by neither fixed effect. For inequality to vary, the income distribution has to change. Thus variation in income inequality across states and time requires variation in the income distribution across states and time. By including income per capita as a control variable, the effect changes in the income distribution have on consumption via income inequality can be distinguished from all other potential effects changes in the income distribution have on consumption, but which are unrelated to the inequality measure. If for example income per capita in one state increases faster than in another state but the share of income going to the Top 10% of the income distribution remains unchanged in both states, this effect is picked up by the coefficient of income per capita, rather then incorrectly attributing any potential effect this has on consumption expenditure to changes in income inequality. Due to the log-log relationship of income per capita and the dependent variable, the coefficient β_2 can be interpreted as an income elasticity. If income per capita increases by 1%, consumption expenditure is estimated to increase by $\hat{\beta_2}$%.

2.3 Baseline Results

Table 1 reports regression results obtained from estimation in US state-level data. Ceteris paribus, a one percentage point increase in the share of income going to the Top 10% is associated with a decline of personal consumption expenditures by 0.115%, as shown in column (1). In the US, the share of income going to the Top 10% increased steadily from 32.7% in 1970 to 50.5% in 2018. According to the estimation results, this increase was quantitatively accompanied by an estimated decline in personal consumption expenditures of 2.05%.

Decomposing consumption into services, durable and non-durable goods shows that the negative relationship between income inequality and consumption expenditure is entirely driven by services (see column (1), column (2) and column (3) of Table 1, respectively). Both durable and non-durable goods consumption is positively correlated with income inequality. Due to services making up a larger share of overall consumption, the negative effect of inequality on service consumption dominates the positive effect of inequality on goods consumption.[3]

[3]On average, service consumption accounts for 65%, durable goods consumption for 12%, and non-durable goods consumption for 23% of total consumption. Over time, the share of service consumption increases, whereas the share of both types of goods consumption decreases. For a visualization, see Figure 4 in the Appendix.

Table 1: *Aggregate Personal Consumption Expenditures and Inequality*

	log(PCE)	log(Services)	log(Durable)	log(Nondurable)
Top 10%	-0.115***	-0.279***	0.213***	0.337***
	(-3.54)	(-7.44)	(3.38)	(6.88)
log(Income pc)	0.488***	0.374***	0.963***	0.513***
	(33.51)	(22.30)	(34.25)	(23.43)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.99	0.99	0.94	0.98
Observations	1,144	1,144	1,144	1,144

Note: The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data from 1997-2018. The variable Top10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Turning next to the effect of income on different expenditure categories, one obvious result is that the estimated coefficient $\hat{\beta_2}$, which resembles an income elasticity, is well below 1 for aggregate total personal consumption expenditure. This finding is based on aggregate data, such that it is not clear, that there is a direct correspondence between the coefficient $\hat{\beta_2}$ and individual income elasticities. Nevertheless, an estimated income elasticity well below one is in line with the central finding by Straub (2019), implying non-homotheticity of preferences. Interestingly, the income elasticity varies considerably across the broad consumption categories. Services have the lowest income elasticity at 0.374, followed by non-durable goods at 0.513 and durable goods at 0.963. This implies that the effect of an overall increase in income per capita will differ across consumption categories.

2.4 Results using German Data

In this section, the robustness of the results reported in Table 1 is tested. This is done by repeating the baseline regression in a panel dataset constructed from the 2003 and 2018 waves of the German EVS. To that end, a Bundesland-quarter level panel is constructed from the 2003 and 2018 German EVS waves. The results from estimating Equation (1) in the EVS panel are reported in Table 2. Compared to the US state-level data, all estimated effects of an increase in income inequality on consumption are much larger in magnitude. The overall negative effect on personal consumption expenditures can be replicated in significance but is five times larger. In the German data, it is not just driven by the negative effect on services, but income inequality is also negatively correlated with the consumption of non-durable goods. The coefficient in the case of durable goods consumption is in this case also positive but insignificant.

Table 2: *Personal Consumption Expenditures and Inequality, EVS Data*

	log(PCE)	log(Services)	log(Durable)	log(Nondurable)
Top 10%	-0.578**	-0.758***	0.853	-0.764***
	(-2.52)	(-3.47)	(0.76)	(-3.37)
log(Income pc)	0.519***	0.511***	0.997**	0.586***
	(6.48)	(6.70)	(2.56)	(7.41)
Quarter FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.98	0.99	0.14	0.91
Observations	127	127	127	127

Note: All variables are based on the German EVS waves from 2003 and 2018. The raw data were used to construct a Bundesland-quarter level panel, which is used for estimation. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

The estimated income elasticities however are similar to those found in US data. This is true both for the size of the elasticities, as well as their ordering with respect to size. Again, services are estimated to have the lowest income elasticity, followed by non-durable goods and finally durable goods. Since this will be important in Section 4.2, note that the estimated income elasticities for services and non-durable goods are not significantly different from each other. A Hausman-style test results in a $p - value = 0.38$.

Overall, the negative relationship between income inequality and personal consumption expenditures found in US state-level data can be replicated in the German EVS data. In both cases, the effect seems to be driven by service consumption. Furthermore, the income elasticities of the consumption categories vary, indicating that the underlying preferences generating such demand patterns are non-homothetic.

3 Theory

The model considered in the following is static. Since there is no time dimension to the model, it abstracts from savings by households. Therefore it is assumed, that households spend all of their income, which consists solely of labor income. There is a mass $N = 1$ of infinitely lived households that are endowed with one unit of labor, which they supply inelastically. There are two types of households, which differ in their skill endowment $s \in \{l, h\}$. Let γ denote the share of the population with skill level $s = h$ and $(1-\gamma)$ denote the share of the population with skill level $s = l$. Aggregating across all individuals, this yields $H = \int h^i di = h \cdot \gamma \cdot N = h \cdot \gamma$ and $L = \int l^i di = l \cdot (1-\gamma) \cdot N = l \cdot (1-\gamma)$. The share γ is assumed to be exogenously given and constant over time throughout the ensuing analysis. Likewise, the skill levels l and s are exogenously given and constant over time. Given different marginal products for the two labor inputs L and H, households potentially receive different levels of labor remuneration and thus income. There is no capital in the model.

3.1 Production

Each consumption good is produced by a different industry, all using a linear production technology. To simplify the exposition, the case of two competitive industries is considered.[4] The two industries $i \in \{1, 2\}$ produce the two different consumption goods C_1 and C_2. Profits in both industries are zero due to perfect competition.

Both industries employ labor, but Industry 1 uses only high-skilled labor H whereas Industry 2 uses only low-skilled labor L. Additionally, the two industries use technology A_i, which is assumed to differ across industries. The two production functions can be specified

[4] The analysis can be extended to the case of I industries, complicating the analysis but not changing the nature of the results derived in the following.

as

$$Y_1 = A_H \cdot H$$
$$Y_2 = A_L \cdot L.$$

The two kinds of labor receive their respective marginal product as remuneration. Let good 2 be the numeraire, and thus $p_2 \equiv 1$ and $p = \frac{p_1}{p_2}$ denote the relative price of good 1. Using the FOCs for the two kinds of labor input, the nominal wage rates paid in the two industries, in terms of the numeraire, can be expressed as the following ratio, which is equivalent to the skill premium:

$$\frac{w_H}{w_L} = \frac{A_H}{A_L} p. \tag{2}$$

The two wage rates and the skill premium depend on the two production technologies A_H and A_L and the equilibrium relative price p, which, among other things, depends on the relative supply of the two kinds of labor L and H. For simplicity, the supply of both kinds of labor is assumed to be constant. Therefore, the skill premium changes if either the relative production technology or relative prices change.[5]

Aggregated nominal income of each household group is given as

$$E_h = w_H \cdot H = Y_1 p$$
$$E_l = w_L \cdot L = Y_2.$$

Note that the income of both groups depends on the respective population share, as $Y_1(H) = Y_1(h \cdot \gamma)$ and $Y_2(L) = Y_2(l \cdot (1 - \gamma))$. Without loss of generality, assume that

[5]Here, production is modeled to take place without capital. Alternatively, both industries could use capital, the total supply and allocation of which across industries is assumed to be constant in the short term. In that case, capitalists would be introduced to the model as a third type of household. Capitalists then supply capital to both industries and receive the return on capital, which they consume outside of the model economy. The production function of Industry 1 in that case is given by $Y_1 = A_H K_H^{\alpha} H^{1-\alpha}$ and that for Industry 2 by $Y_2 = A_L K_L^{\alpha} L^{1-\alpha}$. With capital supply and allocation fixed in the short run and capital returns irrelevant for aggregate consumption, the model dynamics are unchanged by the introduction of capital.

$\frac{E_h}{\gamma} > \frac{E_l}{(1-\gamma)}$ throughout. It is equivalent to stating that income per capita is higher in the group of high skilled households than in the group of low skilled households. Aggregating income across the two household groups yields aggregate production

$$E_h + E_l = Y_1 p + Y_2.$$

3.2 Homothetic Preferences

For the benchmark case, all households, independent of their skill level s, are assumed to have the same CES-utility function. Thus, preferences are homothetic and independent of income levels. Specifically, let

$$\mathcal{U} = \left[\zeta_1^{\frac{1}{\sigma}} c_1^{\frac{\sigma-1}{\sigma}} + \zeta_2^{\frac{1}{\sigma}} c_2^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

describe the utility function of all households. The weight attached to each consumption good is given by ζ_i and σ denotes the elasticity of substitution between goods c_1 and c_2. The consumer's optimization problem can be set up as a maximization over a consumption bundle (c_1^s, c_2^s), subject to the budget constraint $E_s = pc_1^s + c_2^s$, where E_s denotes total expenditure, given by $E_h = w_H \cdot H \cdot p$ and $E_l = w_L \cdot L$. All households face the same set of prices, which they take as given.

$$\max_{c_1^s, c_2^s} \mathcal{L} = \left[\zeta_1^{\frac{1}{\sigma}} (c_1^s)^{\frac{\sigma-1}{\sigma}} + \zeta_2^{\frac{1}{\sigma}} (c_2^s)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{1-\sigma}} - \lambda_s \left[E_s - pc_1^s - c_2^s \right] \quad s \in \{h, l\}$$

The first order conditions with respect to c_1^s and c_2^s are given by

$$\frac{\partial \mathcal{L}}{\partial c_1^s} = (\zeta_1)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} (c_1^s)^{-\frac{1}{\sigma}} + \lambda_s p \stackrel{!}{=} 0$$
$$\frac{\partial \mathcal{L}}{\partial c_2^s} = (\zeta_2)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} (c_2^s)^{-\frac{1}{\sigma}} + \lambda_s \stackrel{!}{=} 0.$$

Together with the budget constraint, the optimal ratio of consumption expenditure can be derived from the FOCs as

$$\frac{c_1^s}{c_2^s} = \frac{\zeta_1}{\zeta_2} p^{-\sigma}. \tag{3}$$

Note that the optimal ratio of consumption expenditure is independent of the type of household. The corresponding price index of one unit of utility is the same for both types of household and given by $\mathcal{P} = \left(\zeta_1 p^{1-\sigma} + \zeta_2\right)^{\frac{1}{1-\sigma}}$. The optimal demand for either good is given as

$$c_1^s = \zeta_1 p^{-\sigma} \cdot \frac{E_s}{\zeta_1 p^{1-\sigma} + \zeta_2}$$
$$c_2^s = \zeta_2 \cdot \frac{E_s}{\zeta_1 p^{1-\sigma} + \zeta_2}.$$

3.2.1 Testable Implications

The optimal ratio of consumption expressed in (3) can be used to derive a structural estimation equation, such that the ratio of preference parameters (ζ_1/ζ_2) and the elasticity of substitution σ can be estimated in consumption data. To do so, both sides of Equation (3) are multiplied by the relative price p to arrive at a ratio of expenditure shares:

$$\frac{\omega_1^s}{\omega_2^s} = \frac{\zeta_1}{\zeta_2} p^{1-\sigma}.$$

Taking the log, this yields an equation which can be estimated.

$$\log\left(\frac{\omega_1^s}{\omega_2^s}\right) = \log\left(\frac{\zeta_1}{\zeta_2}\right) + (1-\sigma)\log(p) \tag{4}$$

3.2.2 Equilibrium

In equilibrium, production factors are paid their marginal product, firms make zero profits, households maximize their utility, and the relative price p is such that the market for both consumption goods clears. Aggregate demand for both goods can be derived by summing demand across skill groups.

$$C_1 = \frac{\zeta_1 p^{-\sigma}}{(\zeta_1 p^{1-\sigma} + \zeta_2)} (E_h + E_l)$$
$$C_2 = \frac{\zeta_2}{(\zeta_1 p^{1-\sigma} + \zeta_2)} (E_h + E_l).$$

Market clearing requires that, for each good, demand be equal to supply

$$Y_1 = C_1 = \frac{\zeta_1 p^{-\sigma}}{(\zeta_1 p^{1-\sigma} + \zeta_2)} (E_h + E_l)$$
$$Y_2 = C_2 = \frac{\zeta_2}{(\zeta_1 p^{1-\sigma} + \zeta_2)} (E_h + E_l).$$

Note, that since preferences are homothetic, the optimal ratio of consumption is equal for both types of households. Furthermore, homothetic preferences imply that the optimal ratio of consumption at the aggregate level is independent of the aggregate level of income and the income distribution. It implies that

$$\frac{C_1}{C_2} = \frac{\zeta_1}{\zeta_2} p^{-\sigma},$$

where C_i denotes the aggregate level of consumption of good i. Therefore, the equilibrium condition can be stated as

$$\frac{Y_1}{Y_2} = \frac{\zeta_1}{\zeta_2} p^{-\sigma}. \tag{5}$$

Since output in both industries is a function of γ, with $Y_1(h \cdot \gamma)$ and $Y_2(l \cdot (1-\gamma))$, the equilibrium condition stated in (5) is an implicit function of γ. For comparative static analyses, the equilibrium can also be stated as a structural equation:

$$F \equiv \frac{A_H \cdot H}{A_L \cdot L} - \frac{\zeta_1}{\zeta_2} p^{-\sigma} = 0. \tag{6}$$

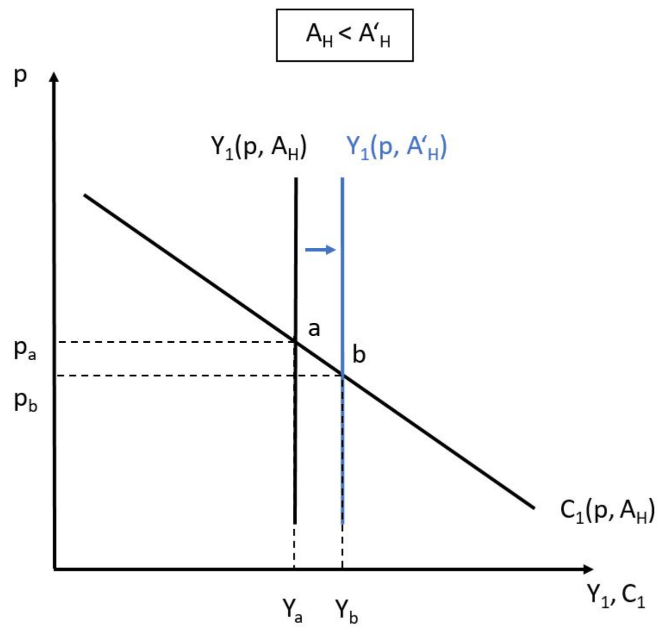


Figure 1: *An Exogenous Positive Increase in* A_H

3.2.3 Comparative Static

Now consider an exogenous increase in A_H and how it affects different aspects of the equilibrium. Firstly, it affects the output of Industry 1, Y_1, which follows directly from the production function. Graphically, this is captured in Figure 1 by the shift of the supply curve of good 1 to the right. The output quantity increases from Y_a to Y_b.

Secondly, the increase in A_H affects equilibrium prices. Graphically, this is captured by the lower relative equilibrium price of good 1, p_b, in Figure 1. Analytically, this can be calculated using the implicit function theorem and Equation (6). For the derivation, see Appendix B.2. Specifically,

$$\frac{dp}{dA_H} = -\frac{\partial F/\partial A_H}{\partial F/\partial p} < 0.$$

Besides affecting the equilibrium quantity and price of good 1, the increase in A_H also affects the income distribution.[6] The effect can best be illustrated with the Gini coefficient.

[6]One example for how a shift in technology can affect income inequality is automation of labor, discussed for example by Acemoglu and Restrepo (2022).

The Gini coefficient is a measure of inequality defined over the domain $G \in [0,1]$, with a value of 1 describing the most unequal distribution of income and a value of 0 describing a completely equal distribution of income. In the case of just two different groups, it is calculated as the (absolute) difference between the income share and the population share of the population group with higher per capita income. Thus, under the premise of $\frac{E_h}{\gamma} > \frac{E_l}{1-\gamma}$, the Gini coefficient can be calculated as

$$G = \frac{A_H H \cdot p}{A_H H \cdot p + A_L L} - \gamma.$$

An increase in A_H unequivocally decreases income inequality for a given γ, as a negative derivative demonstrates:

$$\frac{\partial G}{\partial A_H} = -\frac{H \cdot p \cdot A_L \cdot L(1-\sigma)}{(A_H H \cdot p + A_L L)^2} < 0.$$

The negative sign results from a negative effect of A_H on the income of high-skilled households.[7] This is driven by the price effect, which dominates the scale effect of A_H if and only if $\sigma < 1$ is assumed, which implies that c_1 and c_2 are complements. Evidence for complementarity and thus the assumption that $\sigma < 1$ is presented in Section 4.2. If instead $\frac{E_h}{\gamma} < \frac{E_l}{1-\gamma}$, such that the group of lows skilled workers has a higher income per capita, the increase in A_H increases income inequality.

The ratio of aggregate demand is independent of the income distribution because preferences are homothetic. Therefore, this decrease in inequality is irrelevant to aggregate demand. An exogenous increase in A_H thus only affects the equilibrium by changing the supply side, causing an adjustment in equilibrium prices.

3.3 Non-homothetic Preferences

Deviating from the benchmark case discussed in the previous section, in this section preferences are assumed to be of the non-homothetic CES type. This class of preferences

[7] For a derivation of the effect of A_H on income, see Appendix B.2.

goes back to work by Hanoch (1975) and Sato (1977), who noted that the standard CES function is a very restrictive way to describe preferences. By assuming that preferences are directly explicitly additive, the income effects of all goods are implicitly constrained to be equal to one. Introducing the notion of direct implicit additivity, Hanoch (1975) describes a class of preferences that still exhibit constant elasticity of substitution while allowing for non-constant income effects, resulting in non-homotheticity. Preferences are defined to be directly implicitly additive if the direct utility function is implicitly additive. This class of preferences, also referred to as Implicit CES (Matsuyama (2022)) is growing in popularity in economic research and accordingly has been used to study a variety of economic issues.[8]

Standard assumptions are put on the utility function $\mathcal{U}(\mathbf{c}, \mathcal{I})$, namely that it is continuously and monotonically increasing and concave in income denoted by $\mathcal{I}$, such that $\partial\mathcal{U}(\mathbf{c}, \mathcal{I})/\partial\mathcal{I} > 0$, $\partial^2\mathcal{U}(\mathbf{c}, \mathcal{I})/\partial\mathcal{I}^2 < 0$, and continuously and monotonically increasing in all consumption goods c_i, such that $\partial\mathcal{U}(\mathbf{c}, \mathcal{I})/\partial c_i > 0 \ \forall c_i \in \mathbf{c}$. Due to income effects differing across consumption goods, the utility of household type s can only be implicitly defined as

$$\sum_{i \in I} \left(U_s^{\varepsilon_i} \zeta_i\right)^{\frac{1}{\sigma}} \left(c_i^s\right)^{\frac{\sigma-1}{\sigma}} = 1, \quad i \in \{1, 2\}, \quad s \in (h, l). \tag{7}$$

Within the respective skill groups, households are assumed to be homogeneous. Equation (7) describes an indirect utility function that is already optimized. To see that, note that each summand in Equation (7) corresponds to the optimal expenditure share of the respective consumption good, denoted by ω_i^s. Each summand is therefore equivalent to the optimal expenditure share $\omega_i^s = \left(U_s^{\varepsilon_i} \zeta_i\right)^{\frac{1}{\sigma}} \left(c_i^s\right)^{\frac{\sigma-1}{\sigma}} \ \forall \, i \in I$. Anticipating the discussion on page 22 ff, note that a normalization of the preference parameters $\zeta_i, i \in \{1, 2\}$ and income elasticity parameters $\varepsilon_i, i \in \{1, 2\}$ renders utility as described by (7) cardinal. The same applies to the cost-of-living index denoted by $\mathcal{P}_s$ for each household type $s \in (h, l)$. With U_s and $\mathcal{P}_s$ cardinal, it follows that the utility level of household type s is given by total expenditures E_s divided by the price index $\mathcal{P}_s$, such that $U_s = \frac{E_s}{\mathcal{P}_s}$. Note the different notation used for the

[8]For example, Bohr *et al.* (2021) study directed technical change, Comin *et al.* (2021) look at structural transformation and Fujiwara and Matsuyama (2022) analyze the effect of a technology-gap on premature deindustrialization.

household type specific, and thus carrying a subscript, maximum attainable utility level U_s, and the general utility function $\mathcal{U}(\mathbf{c}, \mathcal{I})$. Only the former will be relevant for the ensuing analysis.

The difference between these preferences and standard homothetic preferences is the weight with which the different consumption goods enter utility. As in the homothetic benchmark case discussed above, the utility weight consists of $\zeta_i^{\frac{1}{\sigma}}$, which varies across consumption goods as indicated by its subscript i. In addition, the weight also consists of $U_s^{\varepsilon_i \cdot \frac{1}{\sigma}}$, which depends on the consumption good specific elasticity parameter ε_i and the utility level U_s, where U_s refers to the maximum utility level obtainable for given income level I and relative prices, as expressed by $p \equiv \frac{p_1}{p_2}$. If income elasticities vary across consumption goods, which is expressed by the subscript i, these preferences are non-homothetic. To see why, note that if the utility level increases, for example due to increased income, the relative weight of the different consumption goods changes if $\varepsilon_1 \neq \varepsilon_2$. As in the standard CES case, σ governs the elasticity of substitution between goods and is assumed to be constant. In the following, the analysis will center around a two-goods scenario. It can be extended to the I goods case, for which the same results can be derived.

The consumer's optimization problem can be set up as a maximization of the implicit utility as defined in (7) over a consumption bundle (c_1^s, c_2^s) subject to a standard budget constraint, where $E_s = pc_1^s + c_2^s$ denotes total expenditure and is given by $E_h = w_H \cdot H \cdot p$ and $E_l = w_L \cdot L$, respectively. As in the homothetic case, all households face the same set of prices, which they take as given.

$$\max_{c_1^s, c_2^s} \mathcal{L} = \left[(U_s^{\varepsilon_1}\zeta_1)^{\frac{1}{\sigma}} (c_1^s)^{\frac{\sigma-1}{\sigma}} + (U_s^{\varepsilon_2}\zeta_2)^{\frac{1}{\sigma}} (c_2^s)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{1-\sigma}} - \lambda_s \left[E_s - pc_1^s - c_2^s \right] \quad s \in \{h, l\}$$

The first order conditions with respect to c_1^s and c_2^s are given by

$$\frac{\partial \mathcal{L}}{\partial c_1^s} = (U_s^{\varepsilon_1}\zeta_1)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} (c_1^s)^{-\frac{1}{\sigma}} + \lambda_s p \stackrel{!}{=} 0$$
$$\frac{\partial \mathcal{L}}{\partial c_2^s} = (U_s^{\varepsilon_2}\zeta_2)^{\frac{1}{\sigma}} \frac{\sigma - 1}{\sigma} (c_2^s)^{-\frac{1}{\sigma}} + \lambda_s \stackrel{!}{=} 0$$

Plugging $\omega_1^s = \left(U_s^{\varepsilon_1}\zeta_1\right)^{\frac{1}{\sigma}} \left(c_1^s\right)^{\frac{\sigma-1}{\sigma}}$ into $\frac{\partial\mathcal{L}}{\partial c_1^s}$ and rearranging yields

$$c_1^s p = \omega_1^s \frac{1}{\lambda_s}\frac{1-\sigma}{\sigma}$$

Note that in the two goods case $\omega_1^s + \omega_2^s = 1$ and $pc_1^s + c_2^s = E_s$. From this it follows that $E_s = \frac{1}{\lambda_s}\frac{1-\sigma}{\sigma}$. Plugging in and rearranging results in an expression for the Hicksian demand. This can be done analogously for good 2, such that the respective Hicksian demands are given by

$$\begin{aligned} c_1^s &= \zeta_1 \left(\frac{E_s}{p}\right)^{\sigma} U_s^{\varepsilon_1} \\ c_2^s &= \zeta_2 E_s^{\sigma} U_s^{\varepsilon_2}. \end{aligned} \tag{8}$$

The price index for one unit of utility is given by $\mathcal{P}_s = \left(U_s^{\varepsilon_1}\zeta_1 p_1^{1-\sigma} + U_s^{\varepsilon_2}\zeta_2\right)^{\frac{1}{1-\sigma}}$. Note that as the ratio of optimal consumption depends on the household type $s \in \{h, l\}$, the price index is different for each household type.

The Marshallian demand for either consumption good can be derived by combining $\frac{\partial\mathcal{L}}{\partial c_1^s}$ and $\frac{\partial\mathcal{L}}{\partial c_2^s}$ and plugging into the budget constraint of the household. The second equality is derived using the definition of $\mathcal{P}_s$ and holds due to normalization of parameters, such that U_s and $\mathcal{P}_s$ are cardinal and $E_s = U_s \cdot \mathcal{P}_s$ holds.

$$\begin{aligned} c_1^s &= \frac{E_s}{\zeta_1 p^{1-\sigma} U_s^{\varepsilon_1} + \zeta_2 U_s^{\varepsilon_2}} \cdot \zeta_1 U_s^{\varepsilon_1} p^{-\sigma} = \zeta_1 U_s^{1+\varepsilon_1} E_s^{\sigma} p^{-\sigma} \\ c_2^s &= \frac{E_s}{\zeta_2 p^{1-\sigma} U_s^{\varepsilon_1} + \zeta_2 U_s^{\varepsilon_2}} \cdot \zeta_2 U_s^{\varepsilon_2} = \zeta_2 U_s^{1+\varepsilon_2} E_s^{\sigma} \end{aligned} \tag{9}$$

The optimal ratio of expenditure shares and consumption goods is given by

$$\frac{\omega_1^s}{\omega_2^s} = \frac{\zeta_1}{\zeta_2} p^{1-\sigma} U_s^{\varepsilon_1-\varepsilon_2} \tag{10}$$

$$\frac{c_1^s}{c_2^s} = \frac{\zeta_1}{\zeta_2} p^{-\sigma} U_s^{\varepsilon_1-\varepsilon_2}. \tag{11}$$

The ratios illustrate the two important features of this form of preferences: One, the constant parameter σ governs the elasticity of substitution between goods. Intuitively, if prices change at the same rate, this cancels out and relative demand is not affected. Only a change in relative prices affects relative demand, and the size and direction of that effect depend on σ, the elasticity of substitution. And two, the expenditure for good c_1 relative to good c_2 increases (decreases) as income and with it the overall utility level U_s increases, if and only if $\varepsilon_1 > \varepsilon_2$ ($\varepsilon_1 < \varepsilon_2$). Thus, goods can be ranked according to their income elasticity parameter ε_i from "most like a necessity" to "most like a luxury". The additional assumption of $\varepsilon_i > 0 \quad \forall\, i \in I$ guarantees that the absolute consumption level of all goods increases as the overall utility level U_s increases. Analytically, the change in the optimal ratio of goods consumption at the household level as utility level U_s changes is given by the derivative of (11) with respect to U_s:

$$\frac{\partial\left(c_1/c_2\right)}{\partial U_s} = \frac{\zeta_1}{\zeta_2} p^{-\sigma} (\varepsilon_1 - \varepsilon_2) \cdot U_s^{\varepsilon_1 - \varepsilon_2 - 1} \tag{12}$$

$$\frac{\partial\left(c_1/c_2\right)}{\partial U_s} = \begin{cases} > 0 \text{ if } \varepsilon_1 > \varepsilon_2 \\ < 0 \text{ if } \varepsilon_1 < \varepsilon_2 \end{cases}$$

3.3.1 Testable Implications

The preference structure given in (7) and the subsequent derivations can be used to derive a structural equation which facilitates testing for non-homotheticity of preferences in consumption data. In addition, the structural equation shows that without loss of generality, all preference parameters ζ_i and expenditure elasticity ε_i can be normalized by dividing by the preference parameter and expenditure elasticity of one good $i \in I = \{1, 2\}$.

The Hicksian demand expressed in (8) can be reformulated to arrive at an expression for U_s. For ease of exposition, this is done for consumption good c_2. Since good 2 is the numeraire good, $\omega_2^s = c_2^s / E_s$ holds. Reformulating yields

$$\varepsilon_2 \log(U_s) = log\left(\frac{\omega_2^s}{\zeta_2}\right) + (1-\sigma)\log(E_s). \tag{13}$$

Taking the log of the optimal expenditure share ratio in (10) and plugging in the expression for U_s derived in (13) results in an expression for the optimal expenditure ratio that is independent of the utility level U_s.

$$\log\left(\frac{\omega_1^s}{\omega_2^s}\right) = (1-\sigma)\log(p) + \left(\frac{\varepsilon_1 - \varepsilon_2}{\varepsilon_2}\right)(1-\sigma)\log(E_s) + \left(\frac{\varepsilon_1 - \varepsilon_2}{\varepsilon_2}\right)\log(\omega_2^s) - \\ - \left(\frac{\varepsilon_1 - \varepsilon_2}{\varepsilon_2}\right)\log(\zeta_2) + \log\left(\frac{\zeta_1}{\zeta_2}\right) \tag{14}$$

The reformulation demonstrates that the optimal expenditure ratio depends on the relative size of the ε_is and ζ_is but not on their absolute value. Thus, any normalization of those parameters is an isoelastic transformation of the utility function and leads to obersvationally equivalent utility maximization outcomes. Therefore, let $\varepsilon_2 \equiv 1$ and $\zeta_2 \equiv 1$. This cardinalizes the utility function and the price index faced by households, such that $E_s = U_s \cdot P_s$ holds.

Equation (14) is used in Section 4.2 to estimate the income elasticity parameters of different consumption goods. The estimation equation is derived by using (for example) good 2 as a base good, such that $\varepsilon_2 \equiv 1$. To clarify notation, the price normalization is abandoned for this example. In that case, (14) simplifies to

$$\log\left(\frac{\omega_1^s}{\omega_b^s}\right) = (1-\sigma)\log\left(\frac{p_1}{p_b}\right) + (\varepsilon_1 - 1)(1-\sigma)\log\left(\frac{E}{p_b}\right) + (\varepsilon_1 - 1)\log(\omega_b^s) - \\ -(\varepsilon_1 - 1)\log(\zeta_b) + \log\left(\frac{\zeta_1}{\zeta_b}\right).$$

Except for the terms $\frac{\zeta_1}{\zeta_b}$ and ζ_b, which will be subsumed in an estimated constant, all terms consisting of parameters can in principle be estimated. Defining one consumption category to be the base category, the equation consists only of observable variables and can be estimated.

Estimating the empirical counterpart of (14) is informative in two respects. If the estimated coefficients of $\log\left(\frac{E}{p_b}\right)$ and $\log(\omega_b^s)$ are statistically significantly different from zero, it indicates that consumer preferences are indeed non-homothetic. This can be seen when comparing Equation (4), derived from the model featuring homothetic preferences, to Equation (14). In addition, the empirical estimates of the preference parameters ε_i and σ will be helpful to determine if the model is consistent with the empirical findings reported in Section 2.

3.3.2 Equilibrium

The model is closed by requiring market clearing. This imposes equality of aggregate demand and aggregate supply in each industry and consumption category. The aggregation process of the demand side is more complex if, as is the case here, preferences are non-homothetic. Taking into account that households within a given skill group are homogeneous, aggregate demand for good i can be derived by summing Marshallian demand, as given by (9), across skill groups.

$$C_1 = c_1^h + c_1^l = \zeta_1 p^{-\sigma}\left(E_h^{\sigma}U_h^{1+\varepsilon_1} + E_l^{\sigma}U_l^{1+\varepsilon_1}\right)$$
$$C_2 = c_2^h + c_2^l = \zeta_2\left(E_h^{\sigma}U_h^{1+\varepsilon_2} + E_l^{\sigma}U_l^{1+\varepsilon_2}\right)$$

From this, the ratio of aggregate demand for the two goods can be derived as

$$\frac{C_1}{C_2} = \frac{\zeta_1}{\zeta_2}p^{-\sigma}\frac{E_h^{\sigma}U_h^{1+\varepsilon_1} + E_l^{\sigma}U_l^{1+\varepsilon_1}}{E_h^{\sigma}U_h^{1+\varepsilon_2} + E_l^{\sigma}U_l^{1+\varepsilon_2}}.$$

In the case of non-homothetic preferences, the ratio of aggregate demand thus depends on the income and expenditure levels of both types of households $E_s,\ s \in (h,l)$, as well as their utility levels U_s and the expenditure elasticities $\varepsilon_i,\ i \in (1,2)$, besides the pure taste parameters ζ_i, and the price ratio. The price ratio is the slack parameter that adjusts to equalize aggregate demand and aggregate supply in the equilibrium.

In general, the ratio of aggregate demand for good 1 and good 2 resulting from non-homothetic preferences differs from the ratio of aggregate demand if preferences are homothetic. Indeed, the ratios coincide if and only if $U_h^{\varepsilon_1} = U_h^{\varepsilon_2} \cap U_l^{\varepsilon_1} = U_l^{\varepsilon_2}$ or $U_h = U_l$. This is equivalent to requiring either $\varepsilon_i = 0 \; \forall \; i \in (1,2)$, or $\varepsilon_1 = \varepsilon_2$, or $U_h = U_l$. The latter is equivalent to both household types receiving exactly the same income per capita and is therefore a special case which is unlikely to be given in reality. $\varepsilon_i = 0 \; \forall \; i \in (1,2)$ implies that the utility level enters the preferences with a power of zero, rendering preferences homothetic. $\varepsilon_1 = \varepsilon_2$ implies that the utility weight of all goods is independent of the utility level, which once again renders preferences homothetic.[9] Therefore, $\varepsilon_1 \neq \varepsilon_2$ in combination with $U_l \neq U_h$ is a sufficient condition for the ratio of aggregate demand given non-homothetic preferences to differ from the ratio of aggregate demand given homothetic preferences.

Market clearing requires that, for each good, demand be equal to supply

$$Y_1 = \zeta_1 p^{-\sigma} \left(E_h^{\sigma} U_h^{1+\varepsilon_1} + E_l^{\sigma} U_l^{1+\varepsilon_1} \right)$$
$$Y_2 = \zeta_2 \left(E_h^{\sigma} U_h^{1+\varepsilon_2} + E_l^{\sigma} U_l^{1+\varepsilon_2} \right).$$

These conditions for the two goods markets can be combined and expressed as a ratio, such that the equilibrium condition can a be stated as

$$\frac{Y_1}{Y_2} = \frac{\zeta_1}{\zeta_2} p^{-\sigma} \frac{E_h^{\sigma} U_h^{1+\varepsilon_1} + E_l^{\sigma} U_l^{1+\varepsilon_1}}{E_h^{\sigma} U_h^{1+\varepsilon_2} + E_l^{\sigma} U_l^{1+\varepsilon_2}}.$$

To facilitate comparative static analyses, the equilibrium can also be stated as a structural equation:

$$F \equiv \frac{A_H H}{A_L L} - \frac{\zeta_1}{\zeta_2} p^{-\sigma} \frac{E_h^{\sigma} U_h^{1+\varepsilon_1} + E_l^{\sigma} U_l^{1+\varepsilon_1}}{E_h^{\sigma} U_h^{1+\varepsilon_2} + E_l^{\sigma} U_l^{1+\varepsilon_2}} = 0. \tag{15}$$

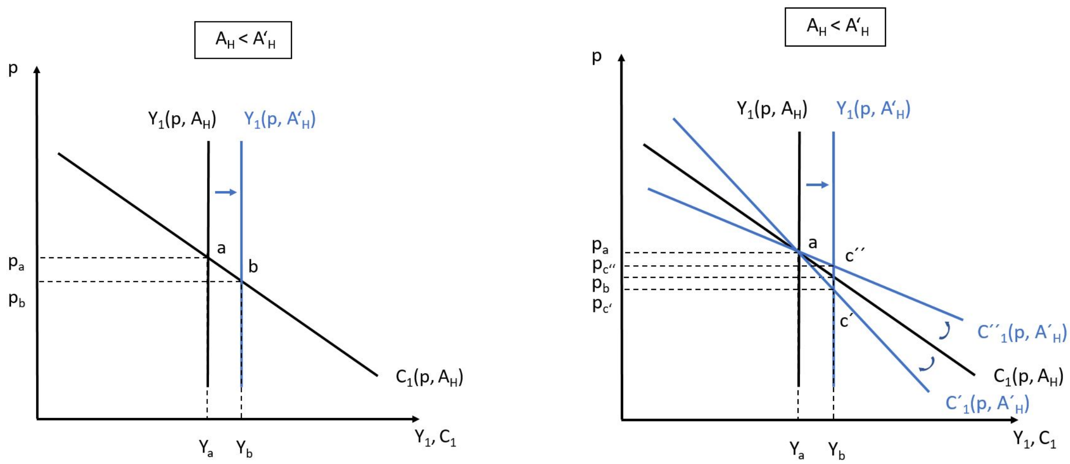
When comparing the structural equations for the case of homothetic preferences (Equation (6)) and non-homothetic preferences (Equation (15)), it is obvious that comparative static analyses are more intricate in the non-homothetic case compared to the homothetic

[9] In the more general I-good case, relative aggregate demand is unaffected by price changes if either $\varepsilon_i = 0 \; \forall \; i$ or $\varepsilon_i = \varepsilon_j \; \forall \; i \neq j$. The same logic applies, such that in both cases preferences are homothetic.

benchmark case. The reason is the income-dependent preference structure.

3.3.3 Comparative Static

Consider again an exogenous increase in production technology of Industry 1, A_H, which results in a higher output of Industry 1, Y_1. This is captured graphically in Subfigure 2a, which is equivalent to Figure 1. Again, the increased supply of Y_1 causes its relative price p to decrease, which is denoted by p_b in Subfigure 2a.



(a) *Supply Side Effect* **(b)** *Demand Side Effect*

Figure 2: *Decomposing the Supply Side Effect and the Demand Side Effect*

As in the case of homothetic preferences, the increase in A_H affects the income distribution. Specifically, income inequality is reduced by the increase in A_H. As preferences are now assumed to be non-homothetic, the change in the income distribution affects aggregate demand. This change in aggregate demand in turn affects equilibrium prices. This channel will in the following be referred to as the demand-side channel. It is illustrated graphically in Subfigure 2b.

In which direction aggregate demand is shifted by the non-homotheticity of preferences is a priori unclear. The sign of the effect depends on the derivative of the non-homothetic part of the structural equation pinning down equilibrium prices with respect to A_H. It also depends on the income and utility levels of the two types of households, as they both depend on A_H. It is thus determined by

$$\partial \left(\frac{E_h^\sigma U_h^{1+\varepsilon_1} + E_l^\sigma U_l^{1+\varepsilon_1}}{E_h^\sigma U_h^{1+\varepsilon_2} + E_l^\sigma U_l^{1+\varepsilon_2}} \right) / \partial A_H \lesseqgtr 0. \tag{16}$$

For the demand side channel to be inactive, it is required that the term is equal to zero. Trivially, this is the case if $\varepsilon_1 = \varepsilon_2$, as in that case aggregate demand is the same under homothetic and non-homothetic preferences. If however $\varepsilon_1 \neq \varepsilon_2$, the term is generally not zero, such that non-homotheticity of preferences is a sufficient condition for the demand-side channel to be active.[10]

Specifically, if the derivative has a positive sign, meaning that demand for good 1 increases relative to demand for good 2 if A_H increases, then $\partial F / \partial A_H$ is lower than if preferences are homothetic. In other words, the equilibrium price $p_{c''}$ given non-homothetic preferences is higher than the equilibrium price given homothetic preferences. As an example, consider an exogenous increase in A_H. The resulting increased output in Industry 1, Y_1, reduces the relative price of good 1. The ensuing change in relative prices leads to adjustments of relative demand. Under the innocuous assumption of $\frac{E_h}{\gamma} > \frac{E_l}{1-\gamma}$ and $\gamma = const$, the change in A_H and relative prices reduces the inequality between h-types and l-types by impacting E_h negatively. This leads to an additional change in aggregate demand due to the non-homotheticity of preferences, the size and direction of which is given by (16). If the derivative given in (16) is positive, the change in income inequality increases relative demand for good 1 more than proportionally. This is equivalent to an anticlockwise rotation of the demand curve, causing an additional upward price adjustment of the relative price p, such that the resulting equilibrium price $p \equiv p_1/p_2$ is higher than the equilibrium price when preferences are homothetic. The negative effect of an increase in A_H on p is in that case ameliorated by the demand-side channel. This corresponds to the line C_1'' in Subfigure 2b. The opposite is true if the derivative in (16) has a negative sign, which corresponds to the line C_1' in Subfigure 2b.

To summarize, the essence of the model can be described as follows. Given a fixed

[10]For more detail and mathematical derivations, see Appendix B.2.

supply of input factors and non-homothetic preferences as described by Equation (7), an exogenous increase in A_H affects the equilibrium price p via two channels. On the one hand, an increased supply of Y_1 results in a decreased equilibrium price p. This is equivalent to the model dynamics if preferences are homothetic and illustrated in Subfigure 2a. On the other hand, the increase in A_H affects the income distribution and with it aggregate demand, which is particular to the model featuring non-homothetic preferences. The demand-side channel also affects the equilibrium price p, which is illustrated in Subfigure 2b by a rotation of the demand curve. The non-homothetic model thus demonstrates how changes in the income distribution affect aggregate demand. It also illustrates how aggregate demand affects equilibrium prices and with it income inequality, suggesting a feedback loop. Ultimately, the direction and size of the demand-side channel and how it affects income inequality is an empirical question.

3.4 Discussion

The purpose of the model described above is to point out the existence of a demand-side channel, which is active if preferences are non-homothetic. This is illustrated by comparing the model dynamics if preferences are non-homothetic to the model dynamics in the benchmark case with homothetic preferences. An active demand-side channel rotates the demand curve but does not affect the supply curve. Therefore, equilibrium prices and expenditure shares are different in the homothetic and non-homothetic models. The direction and magnitude of the demand curve rotation depend on the severity of the non-homotheticity, which in the model can be proxied by $(\varepsilon_1 - \varepsilon_2)$, the difference in income elasticities.

The crucial element for the demand-side channel to be active is a difference in income elasticities between different consumption goods, captured by $(\varepsilon_1 - \varepsilon_2) \neq 0$. However, the effect of the non-homotheticity also depends on the severity of income inequality. With uniformly distributed income, the effect of the non-homotheticity is minimized. An increase in income inequality increases the effect of the non-homotheticity on relative expenditure shares. Thus, the demand-side channel, which is equivalent to a rotation of the demand curve, is an increasing function of income inequality. From this insight, a further testable implication of the model can be derived, namely that the effect of income inequality on consumption categories is, in general, non-linear.

In the analysis above, it is considered how the model dynamics change in reaction to an increase in A_H. This is equivalent to a reduction in income inequality, given that the high-skilled households have higher per capita earnings than the low-skilled households before the increase in A_H. The demand-side channel goes in the opposite direction if the increase in A_H results in higher income inequality. How A_H affects income inequality ultimately depends on the population share of high-skilled workers γ, which for the analysis is held constant. For high levels of γ, the per capita income of high-skilled households can be lower than the per capita income of low-skilled households. In that case, an increase in A_H increases income inequality in the model.

As pointed out before, the juxtaposition of a model with homothetic preferences and a model with non-homothetic preferences allows to test for non-homotheticity of preferences directly. The preference parameters of both the homothetic model and the non-homothetic model can be estimated in suitable data. As the estimation equations derived from the models are quite similar (see Equation (4) and Equation (14)), statistical significance (or lack thereof) of the coefficients indicating non-homotheticity in the underlying preferences is informative as to which model is better equipped to describe the issue of interest in the real world.

4 Estimating Non-homotheticity

Before turning to the estimation of how changes in aggregate demand affect income inequality, the key part of the model, non-homotheticity of preferences, is tested empirically. In Comin *et al.* (2021), an empirical strategy for estimating non-homothetic CES from observable variables is developed. For the proposed estimation approach, data with variation across observations in both consumption quantities and prices is needed. Unfortunately, no data on prices at the state and disaggregation level corresponding to the BEA consumption data is publicly available, impeding such an analysis at the US state level.

Nevertheless, it is possible to estimate expenditure elasticities for the consumption subcategories reported in the BEA data by following the approach of Aguiar and Bils (2015). It can be used to see if expenditure elasticities vary across consumption categories, implying non-homothetic preferences, and results in crude estimates of the size of the different income elasticities.

In addition to estimating expenditure elasticities at the state level, this section also reports non-homotheticity parameters estimated in German EVS data. The aim of that exercise is threefold. One, if there is evidence for non-homotheticity in both US and German data, it emphasizes the necessity for using non-homothetic preferences to model economic relationships if consumer behavior plays a role. Two, the EVS data combined with disaggregated price data allows for the estimation of consumption good specific expenditure elasticities as proposed by Comin *et al.* (2021). And lastly, equipped with estimated expenditure elasticities of the consumption subcategories, the ability of the model proposed in Section 3 to explain the different correlations of subcategories of consumption with income inequality as described in Section 2 can be determined.

4.1 Expenditure Elasticities

Following the approach proposed by Aguiar and Bils (2015), expenditure elasticities for different consumption subcategories are estimated using the same state-level data as in Section 2.[11] By nature of expenditure elasticities, the sum of expenditure elasticities of consumption subcategories weighted by the respective expenditure shares of those subcategories is equal to the expenditure elasticity of the aggregate, which by definition is equal to one. The estimation is a log-linear approximation to Engel curves. As noted for example by Banks *et al.* (1997) and Battistin and Nadai (2015), it is required to include

[11] The proposed approach is changed only slightly to account for the fact that the data used here is not on the household but rather on the state level. Specifically, instead of using a good-time-fixed effect as originally proposed, a time-fixed effect is used instead. Additionally, state-fixed effects are used instead of a vector of demographic controls at the household level proposed in the original paper.

a quadratic term of expenditures in the estimation of Engel curves to arrive at unbiased estimates for expenditure shares. The goal of the estimation here is to infer one elasticity parameter for each consumption category. For the analysis at hand, it is not important how the expenditure elasticity may change along the income distribution. To simplify the interpretation of results it is therefore abstained from using a quadratic expenditure term in the estimation, such that the estimation equation is given by

$$\log(x_{sit}) - \log(\overline{x}_{it}) = \alpha_i + \beta_i \cdot \log(pce_{st}) + FE_{is} + FE_{it} + \varepsilon_{sit}, \tag{17}$$

where x_{sit} is the consumption of good i in state s at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all states. Additionally, state- and time-fixed effects are included in the regression to account for state- or time-specific effects. As the regression is estimated independently for each consumption good category, the state- and time-fixed effects are allowed to vary across consumption categories, as indicated by the subscript i. The coefficient β_i represents the estimated expenditure elasticity for each consumption category.[12]

Table 3: *Estimated Expenditure Elasticities*

	log(Services)	log(Durable)	log(Nondurable)
log(pce)	0.902***	1.571***	0.925***
	(73.51)	(44.56)	(33.00)
Time FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
R^2	1.00	0.94	0.93
Observations	1,144	1,144	1,144

Note: SAEXP Data at the US state level from 1997-2018 is used for estimation. The dependent variable is given by as $\log(x_{sit}) - \log(\overline{x}_{it})$, where x_{sit} is the consumption good i in state s at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all states. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Results are reported in Table 3. The first observation is that the three consumption

[12] In reality, the consumption of different categories is related. To take that into account, the three equations of services, durable and non-durable goods are additionally estimated in a Seemingly Unrelated Regression Estimation. Results are reported in Table 11 in the Appendix. The regression results in exactly the same point estimates for the respective expenditure elasticities. The pertaining estimated confidence intervals are slightly wider, but statistical significance of all coefficients remains unchanged.

categories included in the table are estimated to have different expenditure elasticities. The finding of varying expenditure elasticities supports the modeling choice of non-homothetic preferences. Second, the estimated expenditure elasticities are much higher than the income elasticities reported in Table 1. Intuitively, income elasticities are affected by savings, which decrease the income elasticity of all consumption categories. Expenditure elasticities in contrast are unaffected by savings. If, as is the case here, savings are not the main focus of analysis, expenditure and income elasticities are equally informative, as they provide a ranking of consumption categories along the necessity-luxury spectrum. Indeed, the ranking of consumption categories is similar in Table 1 and Table 3, both suggesting $\varepsilon_{services} < \varepsilon_{nondurable} < \varepsilon_{durable}$. While in Table 1 estimates of income elasticities are reported, which are all lower than one, Table 3 reports expenditure elasticities, which naturally are higher than income elasticities due to excluding the issue of savings and how it affects consumption decisions. Therefore, a comparison of absolute size of income- and expenditure elasticities is not informative in this context.

In contrast to the income elasticities, the inequality between the expenditure elasticity of services and nondurable goods is quite weak in Table 3. Indeed, a Hausman-style test indicates that the two expenditure elasticities are not statistically different ($p - value = 0.65$). Upon further inspection, the slight difference in expenditure elasticity of services and non-durable goods suggested by the results reported in Table 3 is almost entirely driven by housing consumption. The estimated expenditure elasticities for all 15 consumption subcategories with available data are reported in Tables 12, 13, and 14 in the Appendix.

Table 4 reports the results from running the same regression but using the household-level EVS data for estimation. The findings are quite similar to those in the US state-level data. However, in this case, the estimated expenditure elasticities of services and non-durable goods are significantly different, the estimated expenditure elasticity of non-durable goods being lower than that of services. A Hausman test of statistical difference reports a $p - value = 0.00$. The difference in results using aggregated and household-level data could be due to a systematic bias because of aggregation. To address the issue, the estimation

Table 4: *Estimated Expenditure Elasticities, German EVS data*

	log(Services)	log(Durable)	log(Nondurable)
log(pce)	0.876***	1.743***	0.637***
	(523.76)	(250.69)	(238.66)
Time FE	Yes	Yes	Yes
R^2	0.82	0.50	0.63
Observations	84,970	83,986	84,969

Note: German EVS data from 2003 and 2018 at the household level are used for estimation. The dependent variable is given by as $\log(x_{jit}) - \log(\overline{x}_{it})$, where x_{jit} is the consumption good i by household j at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all households. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

is repeated using the panel constructed from the German EVS data. This leads to very similar results as when using the non-aggregated EVS data, which are reported in Table 5. The expenditure elasticities vary even stronger across the consumption categories than when using the raw EVS data. The difference between the service elasticity and non-durable goods elasticity is now larger in magnitude, but no longer statistically significant. That, however, is very likely due to the much-reduced sample size. The $p - value = 0.17$ is quite low, considering the small sample size.

Table 5: *Estimated Expenditure Elasticities, German EVS panel*

	log(Services)	log(Durable)	log(Nondurable)
log(pce)	0.859***	2.811***	0.377***
	(12.08)	(9.41)	(3.00)
Quarter FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
R^2	0.97	0.76	0.78
Observations	128	128	128

Note: All variables are based on the German EVS waves from 2003 and 2018. The dependent variable is given by as $\log(x_{sit}) - \log(\overline{x}_{it})$, where x_{sit} is the consumption good i in Bundesland s at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all Bundslander. The raw data were used to construct a Bundesland-quarter level panel, which is used for estimation. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

4.2 Non-homotheticity in German Data

In the previous section, using US state-level data and German Bundesland-level as well as household-level data, it has already been shown that expenditure elasticities vary across the consumption categories services, durable and non-durable goods. The reported findings are indicative of non-homothetic preferences. In this section, relative income elasticities and the elasticity of substitution, which is constant across consumption categories, are estimated following the approach proposed by Comin *et al.* (2021). The estimation requires prices and consumption quantities to vary at the same level of observation, for example at the state level. Unfortunately, there is no data reporting consumer prices at the level of disaggregation needed to employ the proposed strategy at the US state level. Instead, the parameters of interest are estimated in German EVS data from the 2003 and 2018 waves. The household expenditures reported in the German EVS data can be aggregated into the same consumption categories as the US state-level data.

Using the EVS data for estimation has two advantages. One, it overcomes the missing price data problem inherent in the US state-level data, such that it is feasible to estimate the structural estimation proposed by Comin *et al.* (2021). And two, it complements the findings reported in previous sections. For all relationships analyzed so far, similar results to the ones found in the US state-level data can be reported for the German EVS data as well. That the findings of interest can be found in both US state-level and German household-level data is reassuring. Being able to show that the patterns are present in both data sets speaks to their overall relevance and robustness.

4.2.1 Data

To facilitate the estimation, price data at the household level is necessary. This is achieved by merging the EVS data with official price data reported by the Statistisches Bundesamt. The official price data is derived from the EVS, which results in a perfect correspondence of price data and consumption data categories. The price data is available at a very fine disaggregation level. By taking into account how much of each consumption good a household consumes, the price at the disaggregation level of the 15 consumption categories discussed earlier varies at the household level.[13]

The estimation includes control variables at the household level. Specifically, the household size, age of the head of household, and the number of earners in the household are used. The household size dummy is constructed as follows: it takes on the value of 1 if the household size is smaller than three, the value of 2 if the household size is between 3 and 4, and the value of 3 if there are more than 5 household members. The dummy reporting the number of earners takes on the values of zero, one, and two, where two includes all households which have at least two earners.

4.2.2 Estimation Strategy

For estimation, the strategy developed in Comin *et al.* (2021) is used. They demonstrate how the relative income elasticity and constant elasticity of substitution across consumption categories can be estimated in a structural equation. It is equivalent to Equation (14) derived in Section 3.3.

The substitution parameter σ as well as the income elasticity parameters ε_i can be estimated using the following equation:

$$\log\left(\frac{\omega_{i,n}}{\omega_{b,n}}\right) = (1-\sigma)\log\left(\frac{p_{i,n}}{p_{b,n}}\right) + (1-\sigma)(\varepsilon_i - 1)\log\left(\frac{E_n}{p_{b,n}}\right) + (\varepsilon_i - 1)\log(\omega_{b,n}) + \\ + \beta_i' X_n + v_{i,n}$$

$\omega_{i,n}$ is consumption category i's share of total consumption by household n and $\omega_{b,n}$ is the share of total consumption spend on the base consumption category b by household n. Likewise, $p_{i,n}$ denotes the price of consumption category i faced by household n and $p_{b,n}$ the price of the base consumption category b faced by household n. E_n denotes total expenditure on consumption by household n and X_n is a vector of household-specific characteristics, which are a dummy measuring the household size, the age of the head of household, and

[13] Figure 5 in the Appendix illustrates the construction of household-level price data.

a dummy denoting the number of earners in the household. In addition, a year dummy is included to account for the fact that the data comes from two waves of the EVS. It is included to control for year-fixed effects.

The structural equation is estimated using a Generalized Method of Moments (GMM) estimator. It allows imposing constraints on the estimated coefficients, which makes the estimation feasible. Following Aguiar and Bils (2015) and Comin *et al.* (2021), total household expenditure is instrumented for by total household income and the quintile of the income distribution in which the household's income lies. This is done to minimize the effect measurement error has on overall household expenditure, which is calculated by aggregating all reported expenditures. Household income is determined in a separate survey question and is likely to be measured with less error. As household income is correlated with household expenditures, it provides a valid instrument for total expenditure, without the inherent measurement error.

4.2.3 Results

Estimation results are reported in Table 6. The estimation can be used to infer *relative* expenditure elasticities, relative referring to the expenditure elasticity of the base category b. In each column of Table 6, the estimation results from using the category which denominates the column as a base category are reported. If, for example, expenditures on non-durable goods are used as a base category, its expenditure elasticity is normalized to one, which results in the table entry $\varepsilon_{non-dur} - 1 = 0$. Relative to that, the expenditure elasticity of services is higher at $\varepsilon_{services} - 1 = 0.23$ and that of durable goods even higher at $\varepsilon_{durable} - 1 = 1.04$. The overall substitution parameter is estimated to be $\sigma = 0.29$, indicating that all goods are complements.

The estimation is carried out using each of the three broad consumption categories in turn as the base category. The three estimates of the substitution parameter are reasonably similar in size and, importantly, all indicate that the consumption categories are complements. Furthermore, the ordering of the expenditure elasticities is consistent across the use of

Table 6: *Estimating Income Elasticities in German EVS data*

	Non-durable	Services	Durable
σ	0.29	0.45	0.23
	[0.271, 0.316]	[0.431, 0.474]	[0.195, 0.265]
$\varepsilon_{non-dur} - 1$	0	-0.21	-0.81
		[-0.214, -0.200]	[-0.836, -0.782]
$\varepsilon_{services} - 1$	0.23	0	-0.46
	[0.220, 0.238]		[-0.483 -0.442]
$\varepsilon_{durable} - 1$	1.04	0.51	0
	[1.019, 1.070]	[0.495, 0.528]	

Note: Estimation in German EVS data from the 2003 and 2018 waves. Results are derived using a GMM estimator. 95%-confidence intervals are reported in brackets.

different base categories. Since only relative expenditure elasticities are estimated, variations in the size of the estimated expenditure elasticities are irrelevant.

Taken together, the results from estimating expenditure elasticities using two different estimation approaches in two different data sets indicate that expenditure elasticities vary across consumption categories. Furthermore, the expenditure elasticities can quite consistently be ranked to increase from non-durable goods, over services to durable goods consumption, such that $\varepsilon_{non-dur} < \varepsilon_{services} < \varepsilon_{durable}$. This suggests that the model proposed in Section 3 is consistent with the pattern found in Section 2. If income inequality increases, low-income households increase their relative consumption of non-durable goods and reduce their relative consumption of durable goods and services. High-income households instead increase their relative consumption of durable goods and reduce their relative consumption of non-durable goods and services if there is an increase in inequality. At the aggregate level, this results in increased consumption of both durable and non-durable goods and decreased consumption of services. Note that this analysis, as well as the model, abstracts from the effects increases in income inequality have on the level of aggregate consumption due to differences in the propensity to save. It is possible to include that channel in the model by treating saving as another consumption good with a high expenditure elasticity. This extension of the model is described in Appendix B.1.

4.3 Estimating Non-linearity of Income Inequality Effects

As discussed in Section 3.4, the model predicts that the magnitude of the demand-side channel depends on the severity of income inequality. From this, a testable implication arises, namely that income inequality has a non-linear effect on the expenditure shares of different consumption goods.

The most straightforward way to test the model implication is by running regressions similar to those specified in Equation (1). The only difference is, that in addition to a linear term of the inequality measure, the estimation equation includes an additional quadratic term of the inequality measure.

$$log(Exp. - share_{s,t}) = \alpha + \beta_1 \cdot Top10\%_{s,t} + \beta_3 \cdot (Top10\%_{s,t})^2 + \beta_2 \cdot log(Income_{s,t}) + \\ + FE_s + FE_t + \varepsilon_{s,t} \quad (18)$$

The dependent variable in that case is the log of expenditure share for different consumption categories. The expenditure share is calculated as the expenditure of category i in state s and year t divided by total personal consumption expenditures in state s and year t. The model predicts that the estimated coefficient $\hat{\beta}_3$ is significantly different from zero.

The BEA data reports expenditures on 15 different subcategories of consumption. Regression results are reported in Tables 15, 16, and 17 in the Appendix. In 14 out of 15 regressions, the estimated coefficient $\hat{\beta}_3$ is statistically different from zero, indicating that the relationship between expenditure shares and income inequality is indeed non-linear for all consumption categories, except housing. This finding is in line with the prediction made by the model discussed in Section 3.

5 Quantifying the Demand-side Channel

The model described in Section 3 illustrates how an exogenous increase in income inequality can change aggregate consumption. If the production of consumption goods differs with respect to the skill premium paid in the producing industries, these changes in aggregate consumption affect the economy-wide skill premium. The demand channel can therefore amplify or attenuate the exogenous shock to income inequality. Increases in income inequality have been well documented. In Section 2, the effects of rising income inequality on aggregate demand have been explored. This section in turn will analyze how the demand shift caused by increased income inequality affects the skill premium paid and thus wage inequality. The effect size and direction is a priori unclear. On the one hand, increased income inequality may shift demand towards sectors with a relatively low skill premium, thereby attenuating income inequality. On the other hand, increased inequality can reinforce income inequality if it shifts demand towards goods produced predominantly in sectors paying a high skill premium.

To estimate the size and direction of a demand-side channel on income inequality, information on the skill premium at different levels of aggregation is needed. First, wage inequality at the industry level, and second, wage inequality at the consumption category level has to be known or estimated. Additionally, the change in demand at the consumption good level due to an increase in income inequality has to be known. The last part has already been estimated in Section 2. The goal of this section is to calculate the wage inequality at the industry and consumption category levels. To do so, the skill premium at the industry level has to be aggregated first at the consumption category level and then at the economy-wide level. In the aggregation process, it is crucial to use appropriate weighting schemes.

5.1 Data

This section describes how different data sets are merged to arrive at a mapping of skill use at the industry level, where it is routinely recorded, to the consumption category level. It follows the approach proposed and described by Buera *et al.* (2022).

A reliable measure of wage inequality is the skill premium paid in different industries. Information on skill use at the industry level is made available by EU KLEMS for different countries and years.[14] In the following, data on US industries in 2008 is used for analysis. At

[14]The data can be downloaded from `https://dataverse.nl/dataset.xhtml?persistentId=doi:10.34894/MGSB4H`

the isic3 industry level, the employment- and wage share of three different skill levels in total industry employment is reported. The educational attainment of workers is classified into "University graduates" "Intermediate" and "No formal qualifications". The skill premium at the industry levels is constructed by dividing the wage share of university graduates by their employment share.

To map the skill use at the industry level to the consumption category level, consumption goods categories have to be matched to industry levels. The BEA provides a mapping of Personal Consumption Expenditures categories along NIPA lines to NAICS codes at the industry level.[15] The most recent such mapping is available for 2012. For example, all the industry sectors contributing to the final consumption category "Vehicles" and their respective input values are listed.

To merge the labor input data provided by EU KLEMS with industry output data provided by the BEA, isic3 codes have to be mapped to NAICS codes. While no official mapping between isic3 and NAICS codes exists, there is a clear correspondence in almost all cases. By matching the industry codes used in the EU KLEMS data to NAICS codes used in the BEA dataset, the use of high- medium- and low-skilled labor, the respective wage shares, and the resulting skill premium can, in principle, be calculated at the consumption good level.

5.2 Weighting

In general, the production of the consumption categories considered requires input from different industries. Ideally, the skill premium at the consumption category level would be calculated as a weighted sum of the skill premium paid in the input industries, the weight consisting of the labor intensity of an input industry and its input share at the consumption good level. Unfortunately, EU KLEMS does not report labor intensity or overall employment numbers at the industry level, preventing the implementation of this first-best solution.

Still, there are two feasible approaches to aggregate the skill premium paid in input

[15]Source: `https://www.bea.gov/industry/industry-underlying-estimates`

sectors to the consumption good level. One, the skill premium at the industry level can be weighted by that industry's share in overall input used for the production of a consumption category. In that case, the labor intensity at the industry level is disregarded in the calculation. Two, the skill premium at the industry level can be weighted by that industry's share of the total value added produced by all input industries. This approach yields a good approximation of the first best solution under the assumption that value-added and labor intensity are positively correlated. However, it does not take into account the share of input coming from the single industries at the consumption good level. As a last, additional, approach to calculating the skill premium at the consumption good level, the average of the two previously described skill premium measures can be taken at the consumption category level. In the absence of an economically meaningful guideline as to how to best calculate the average of the other two weights, both receive, somewhat arbitrarily, equal weight. In mathematical terms, the three calculations can be formalized as follows:

$$\text{skill premium}_{Input,i} = \sum_{j}^{J} \frac{input_{j,i}}{input_i} \cdot \text{skill premium}_j,$$

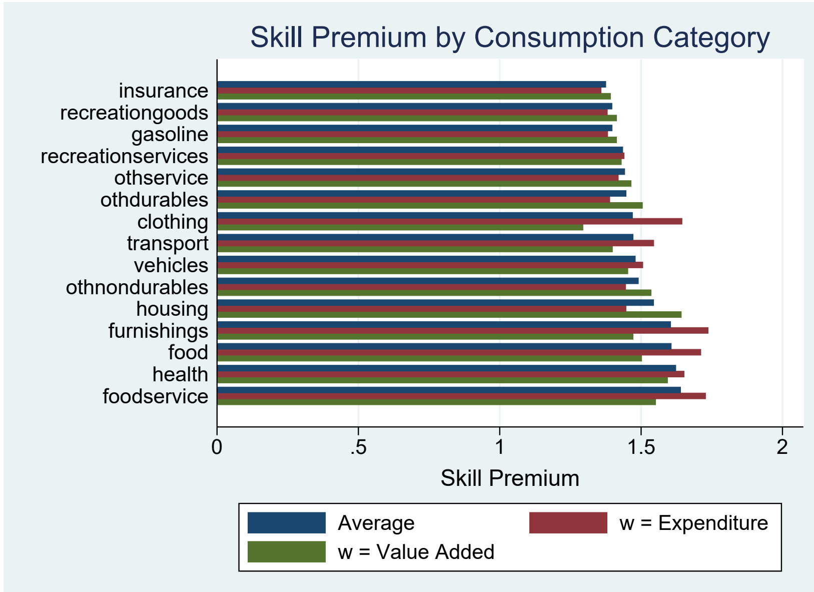
where $input_i$ is the sum of all inputs used to produce consumption category i and $input_{j,i}$ is the input of industry j used by consumption category i.

$$\text{skill premium}_{VA,i} = \sum_{j}^{J} \frac{VA_j}{VA_i} \cdot \text{skill premium}_j,$$

where VA_i is the sum of value added by all industries which are used to produce consumption category i. Finally, taking the average results in

$$\text{skill premium}_{mean,i} = \frac{1}{2}\left(\text{skill premium}_{VA,i} + \text{skill premium}_{Input,i}\right).$$

Depending on the weighting scheme, the skill premium associated with the different consumption categories varies slightly. The mean across all consumption categories ranges from 1.47 to 1.52. The consumption category associated with the lowest skill premium



This figure provides a graphical illustration of skill premium associated with each consumption category considered. The red bars refer to the skill premium calculation using expenditure weights for the accumulation across industries. The green bars refer to skill premium calculation using value added weights for the accumulation across industries. The blue bars show the average of the two skill premium calculations at the consumption category level.

Figure 3: *Calculated Skill Premium in the US for Different Consumption Categories*

according to the average measure is insurance, with a skill premium of 1.38, and the highest average skill premium is 1.64, paid for providing food services. The sensitivity to the weighting scheme used for aggregation is surprisingly low.[16] The three different measures of the skill premium at the consumption good category level are depicted in Figure 3.

5.3 Quantification

We are now equipped with a skill premium measure at the consumption category level. From Section 2, the marginal effect an increase in income inequality has on the demand for 15 different consumption categories is known. Combining those two statistics, it can be calculated how an exogenous increase in income inequality affects the economy-wide skill premium by aggregating the changes in demand for each consumption category.

[16]Using weights derived from value-added results in a coefficient of variation of 0.09, which is higher than that of the calculated skill premium when using input share weights, in which case it is 0.06.

The marginal effect increased consumption of a specific consumption category c_i has on the overall skill premium paid in the economy can now be calculated as

$$\frac{\partial \text{ Skill Premium}}{\partial c_i} \approx \text{skill premium}_i - \frac{\sum_{j \neq i}^{J} \text{skill premium}_j \cdot w_j}{\sum_{j \neq i}^{J} w_j} \tag{19}$$

where skill premium$_i$ refers to the skill premium paid in the production of consumption category i. Intuitively, the effect an increased consumption of good i has on the economy-wide skill premium depends on the difference between the skill premium in that category and the (weighted) skill premium in all other categories. The skill premia associated with the production of all other consumption categories should be weighted in the aggregation process, which is expressed by including the weights w_j in Equation 19. Analogously to before, two economically meaningful weights are worth considering. One, a consumption category's share of total consumption, and two, a consumption category's share of total value added. The first weight takes into account how important each category is for aggregate demand, reflecting the overall resources going into producing the goods in each consumption category. The second weight is likely to be a more specific measure of labor input. It is unclear which, if any, of the two weighting schemes is preferable. In any case, the weighting schemes are positively correlated with a correlation coefficient of $\rho = 0.24$. A third weighting scheme can be constructed by using the average of the two possible weighting schemes. This average weight has a correlation of $\rho = 0.81$ with the consumption share weight and a correlation of $\rho = 0.77$ with the value-added weight.[17]

The marginal effect an increase in income inequality has on demand for consumption category i has been estimated in Section 2. The overall effect an increase in income inequality has on the skill premium can thus be approximated by the following calculation:

$$\frac{\partial \text{ Skill Premium}}{\partial \text{ Inequaltiy}} \approx \sum_{i}^{I} \frac{\partial \text{ Skill Premium}}{\partial c_i} \cdot \frac{\partial c_i}{\partial \text{ Inequality}}$$

[17]The three different weights are constructed as follows: $w_{Exp} = \frac{c_i}{\sum_i^I c_i}$, where c_i refers to the consumption of category i; $w_{VA} = \frac{VA_i}{\sum_i^I VA_i}$, where VA_i is the value added produced by all industries contributing to producing good i; $w_{mean} = \frac{1}{2}\left(w_{Exp} + w_{VA}\right)$.

As discussed previously, two possible weighting schemes can be applied when summing across input industries and also consumption categories. Taking the average of these two weighting schemes generates a third weighting scheme. The estimates for the effect a change in aggregate demand has on the economy-wide skill premium using the three different weighting schemes are very similar and reported in Table 7. The estimated effect size of the demand side channel is in the range of $[-0.22; -0.20]$. The effect of an exogenous increase in income inequality by 1 percentage point, via the demand channel, thus is estimated to reduce the overall skill premium by 0.2 percentage points. Changes in aggregate demand hence attenuate changes in income inequality.

Table 7: *Results from Quantifying the Demand Side Channel*

	Weighting Scheme		
	Expenditure	Value Added	Average
$\frac{\partial \text{ Skill Premium}}{\partial \text{ Inequaltiy}}$	-0.200	-0.215	-0.199

Note: Data from EU KLEMS and the BEA are combined to estimated marginal effects of income inequality on consumption categories and, subsequently, the aggregated skill premium. The aggregation is carried out using three different weighting schemes; the result of each is reported in the thus named column.

The results of this back-of-the-envelope quantification suggest that the additional effect the demand side channel has on aggregate demand reduces the the effect of exogenous shifts in income inequality. Both the size and the direction of the effect seem reasonable. It would be surprising to find that the additional effect caused by the demand side channel is larger than the exogenous shock triggering the changes in aggregate demand. Therefore, an effect size smaller than one is in line with intuition. Regarding the direction of the effect, no theoretical prior exists. Depending on the expenditure elasticities and skill premia paid in the producing industries, an attenuation or amplification of the original shift is possible.

Based on the quantification results, industries in which a lower skill premium is paid apparently benefit from the shift in consumption correlated with increased income inequality. The changed consumption composition thus attenuates income inequality. From 1970 to

2018, income inequality increased by 17.8 percentage points in the US. This implies that the economy wide skill premium increased by 3.56 percentage points *less* due to the demand-side channel.

5.4 Discussion

The quantification done in the previous section can only be regarded as a first-order approximation of the potentially non-linear effect of income inequality on expenditures. Indeed, including a quadratic term of the income inequality measure in the regressions discussed in Section 2 suggests that the effect of income inequality on consumption expenditures is non-linear for almost all consumption categories, as indicated by highly significant coefficients of the quadratic term. This is visualized in Figure 6 in the Appendix.

An increase in the inequality measure by 17.8 points cannot be considered a marginal increase. Therefore, using estimated marginal effects to calculate the effect inequality has on the skill premium through changes in consumption expenditures can only result in a crude approximation of the true effect. The aim of the analysis carried out above is to sense the order of magnitude that is plausible. So while the quantification exercise is unlikely to reveal the exact size of the demand side channel, it is nevertheless informative. Besides providing a first approximation of both the size and the direction of the true effect, it demonstrates the existence of the proposed demand-side channel and with that highlights a so far under-researched aspect of inequality.

6 Conclusion

In conclusion, this paper has delved into the intricate relationship between aggregate demand, non-homothetic preferences, and income inequality. By conducting different empirical analyses and using a model to on the one hand explain novel empirical findings and on the other hand derive further testable implications from it, the multifaceted dynamics and interdependencies among these factors were uncovered.

The analysis reveals that income inequality is related to both the magnitude and composition of aggregate demand. In the first step, the relationship between income inequality and aggregate demand is estimated empirically. There is evidence for the expected negative relationship. This addresses the first aspect of how income inequality affects aggregate demand if preferences are non-homothetic, namely that it influences the overall level of aggregate demand. As a byproduct of that analysis, the interesting pattern of the reduction in aggregate demand being exclusively due to decreased service consumption is detected. This addresses the second aspect of how income inequality can affect aggregate demand, namely by changing the composition of aggregate demand.

Focusing on that second aspect, a theoretical model is proposed featuring non-homothetic preferences and linking income inequality and aggregate demand. It can explain the finding of an unequal response to changes in income inequality across consumption categories. This is conditional on income elasticities increasing in a certain order, for which there is indeed evidence in US and German data. The model also illustrates how changes in aggregate demand can have profound implications for specific industries and sectors and, relatedly, income inequality. A change in the composition of demand can potentially amplify or ameliorate a first shock to inequality by affecting the average skill premium paid in the economy. This demand side channel emphasizes that income inequality and non-homothetic preferences should be considered not only in the context of their impact on aggregate demand but also in their role as potential drivers of structural change.

By combining different data sets, a back-of-the-envelope calculation to quantify the demand side channel is done. It suggests that a 1 percentage point increase in income inequality reduces wage inequality by 0.2 percentage points via the demand side channel. While the quantification is insightful and gives a first impression of the effect size and direction, its exact value is of secondary importance. The main purpose of the quantification exercise is to illustrate the existence of the demand side channel and to emphasize the conceptual contribution made in this paper by pointing out its existence in the first place.

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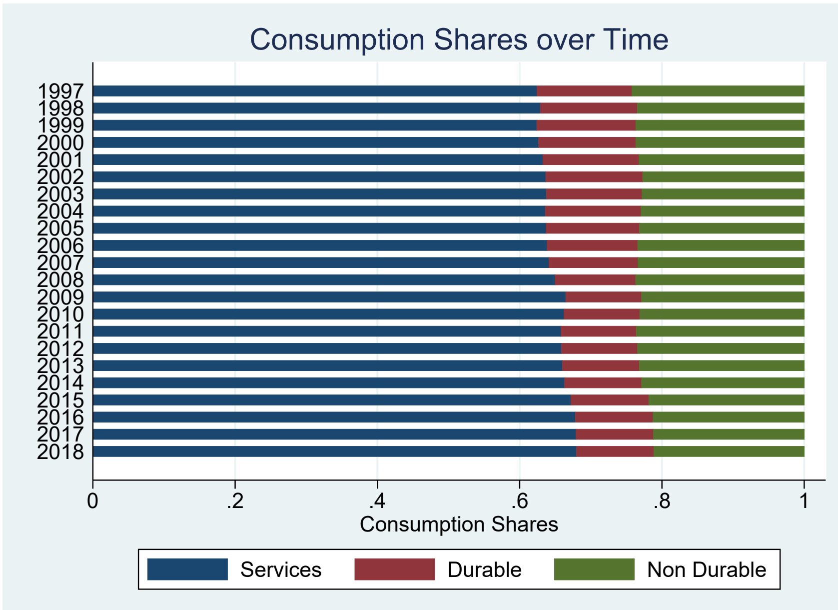
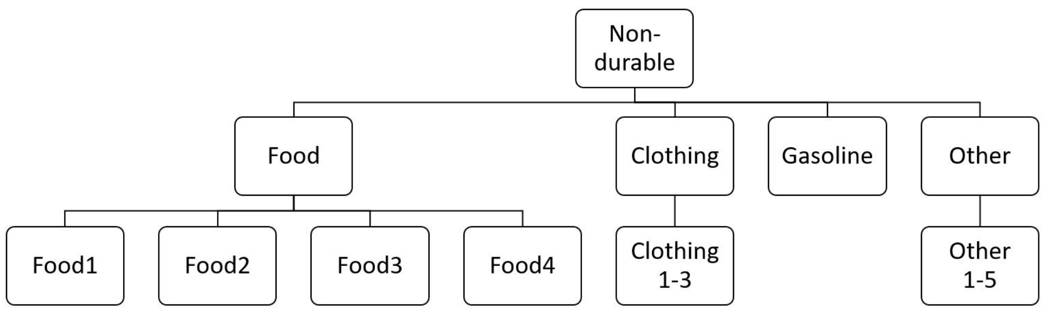
A General Appendix

A.1 Additional Graphs



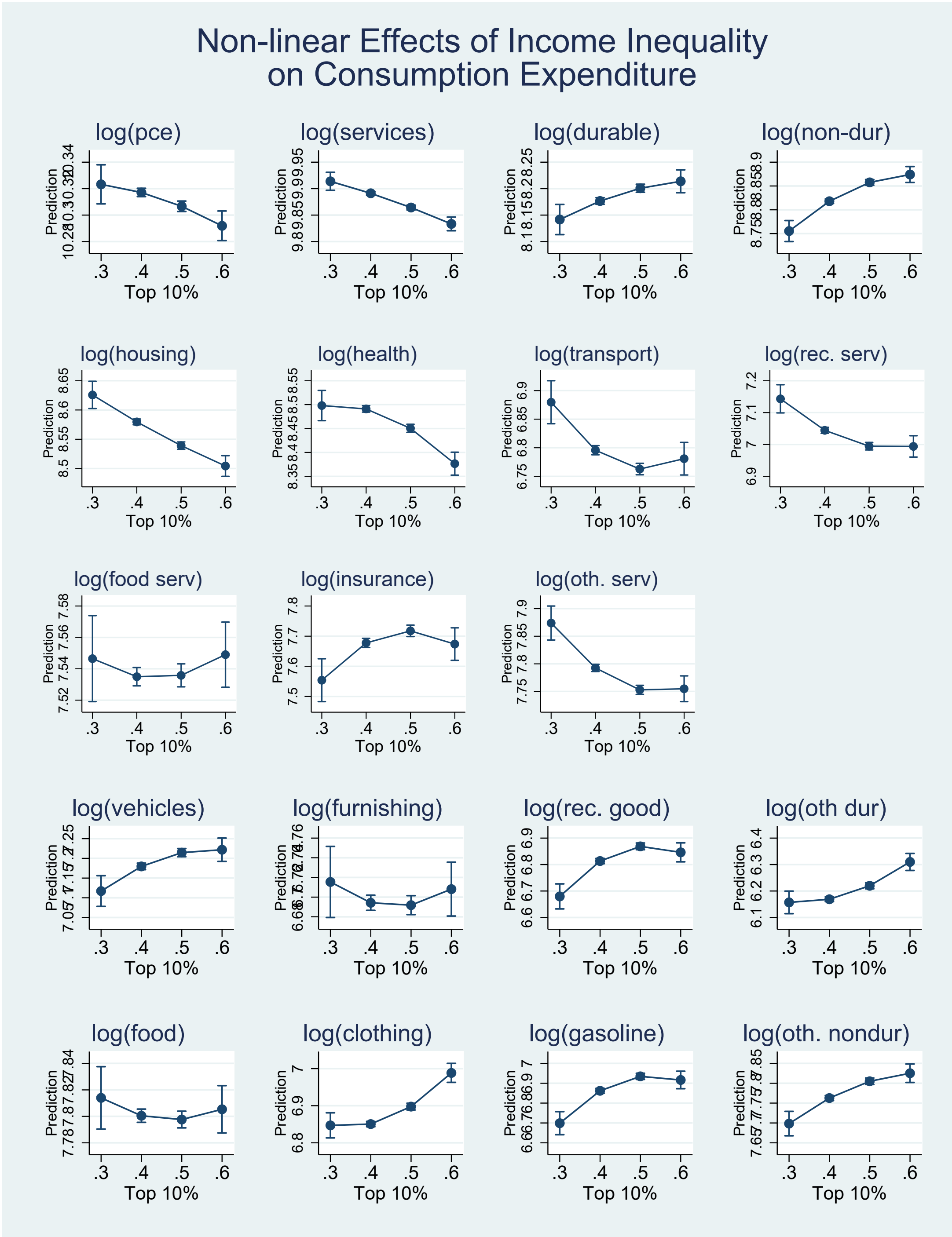
This figure provides a graphical illustration of how the consumption shares of services, durable and non-durable goods changed over time. Data is taken from the BEA.

Figure 4: *Visualization of Consumption Shares over Time*



This figure illustrates why the price for one consumption category (in this example non-durbale goods) faced by households varies at the household level. Because the sub-categories Food1, Food2, Food3 and Food4, which have different prices, may be consumed in different quantities by households, the resulting price index for food and non-durable goods varies at the household level.

Figure 5: *Construction of Household-level Price Data*



This figure provides a graphical illustration of the non-linear effect income inequality has on different consumption subcategories. The logged consumption categories are regressed on a linear and a quadratic term of the variable Top 10%, which measures the share of income going to the top 10% of the income distribution. Additionally, log income per capita and state and year fixed effects are included. Consumption expenditure data is taken from the BEA from 1997-2018 and income inequality data from Mark Frank.

Figure 6: *Visualization of Non-linearity in the Inequality-Consumption Expenditure Relationship*

A.2 Additional Regression Results

A.2.1 Inequality Regressions for Sub-Categories

Table 8: *Personal Consumption Expenditures and Inequality, Durable Goods*

	log(Vehicles)	log(Furnishing)	log(Recreation)	log(Other)
Top 10%	0.279***	0.024	0.355***	0.609***
	(3.24)	(0.29)	(3.36)	(6.46)
log(Income pc)	1.115***	1.206***	0.952***	0.303***
	(28.94)	(33.82)	(20.13)	(7.18)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.86	0.92	0.90	0.95
Observations	1,144	1,144	1,144	1,144

Note: The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data form 1997-2018. The variable Top 10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 8 reports the regression results for subcategories of durable consumption on income inequality, measured by the share of income going to the Top 10% of the income distribution, income per capita, and time- and state-fixed effects.

Table 9 reports the regression results for subcategories of non-durable consumption on income inequality, measured by the share of income going to the Top 10% of the income distribution, income per capita, and time- and state-fixed effects.

Table 10 reports the regression results for subcategories of service consumption on income inequality, measured by the share of income going to the Top 10% of the income distribution, income per capita, and time- and state-fixed effects.

Table 9: *Personal Consumption Expenditures and Inequality, Non-durable Goods*

	log(Food)	log(Clothing)	log(Gasoline)	log(Other)
Top 10%	-0.002	0.583***	0.494***	0.366***
	(-0.03)	(7.74)	(3.81)	(5.40)
log(Income pc)	0.351***	0.415***	0.532***	0.402***
	(15.10)	(12.34)	(9.18)	(13.25)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.97	0.74	0.95	0.97
Observations	1,144	1,144	1,144	1,144

Note: The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data form 1997-2018. The variable Top 10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 10: *Personal Consumption Expenditures and Inequality, Service Goods*

	log(Housing)	log(Health)	log(Transport)	log(Recreation)	log(Food)	log(Insurance)	log(Other)
Top 10%	-0.391***	-0.491***	-0.199**	-0.373***	0.040	0.186	-0.291***
	(-7.60)	(-6.99)	(-2.38)	(-3.80)	(0.66)	(1.18)	(-4.24)
log(Income pc)	0.172***	0.286***	1.020***	0.593***	0.715***	0.607***	0.187***
	(7.51)	(9.11)	(27.23)	(13.54)	(26.46)	(8.59)	(6.10)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.98	0.98	0.92	0.95	0.98	0.89	0.96
Observations	1,144	1,144	1,144	1,144	1,144	1,144	1,144

Note: The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data form 1997-2018. The variable Top 10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

A.2.2 Expenditure Elasticities, different Specification and Subcategories

Table 11: *Estimated Expenditure Elasticities using SURE*

	log(Services)	log(Durable)	log(Nondurable)
log(pce)	0.902***	1.571***	0.925***
	(76.01)	(46.08)	(34.12)
Time FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
R^2	1.00	0.94	0.93
Observations	1,144		

Note: SAEXP Data at the US state level from 1997-2018 is used for estimation. Results are obtained running a seemingly unrelated regression estimation. This is the reason for why observations are only reported in the first column. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 11 reports results corresponding to the ones reported in Table 3 in Section 4.1. Here, the the single estimations for each consumption category is estimated in a Seemingly Unrelated Regression Estimation. The resulting expenditure elasticities are not affected. Only the t-statistics are slightly lower, which does not affect significance, though.

Table 12: *Estimated Expenditure Elasticities, Durable Goods*

	Vehicles	Furnishing	Recreation	Other
log(pce)	1.739***	1.696***	1.556***	1.034***
	(32.61)	(31.35)	(23.58)	(18.53)
Constant	-16.878***	-16.652***	-15.437***	-10.289***
	(-32.57)	(-31.69)	(-24.08)	(-18.98)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.89	0.89	0.93	0.95
Observations	1,144	1,144	1,144	1,144

Note: SAEXP Data at the US state level from 1997-2018 is used for estimation. The dependent variable is given by as $\log(x_{sit}) - \log(\overline{x}_{it})$, where x_{sit} is the consumption good i in state s at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all states. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 12, Table 13 and Table 14 report estimated expenditure elasticities for subcategories of consumption.

Table 13: *Estimated Expenditure Elasticities, Non-durable Goods*

	Food	Clothing	Gasoline	Other
log(pce)	0.579***	0.695***	1.370***	0.806***
	(17.57)	(14.08)	(17.59)	(19.40)
Constant	-5.716***	-6.834***	-13.391***	-7.763***
	(-17.84)	(-14.25)	(-17.70)	(-19.23)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.94	0.94	0.93	0.91
Observations	1,144	1,144	1,144	1,144

Note: SAEXP Data at the US state level from 1997-2018 is used for estimation. The dependent variable is given by as $\log(x_{sit}) - \log(\overline{x}_{it})$, where x_{sit} is the consumption good i in state s at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all states. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 14: *Estimated Expenditure Elasticities, Service Goods*

	Housing	Health	Transport	Recreation	Food	Insurance	Other	Services wo Ho.
log(pce)	0.524***	0.742***	1.528***	0.856***	1.016***	1.836***	0.324***	1.011***
	(16.67)	(17.25)	(28.32)	(13.26)	(25.28)	(20.24)	(7.24)	(60.73)
Constant	-5.404***	-7.338***	-15.300***	-8.544***	-10.115***	-17.940***	-3.537***	-10.064***
	(-17.68)	(-17.55)	(-29.20)	(-13.62)	(-25.90)	(-20.36)	(-8.13)	(-62.20)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.98	0.94	0.98	0.95	0.95	0.90	0.99	0.99
Observations	1,144	1,144	1,144	1,144	1,144	1,144	1,144	1,144

Note: SAEXP Data at the US state level from 1997-2018 is used for estimation. The dependent variable is given by as $\log(x_{sit}) - \log(\overline{x}_{it})$, where x_{sit} is the consumption good i in state s at time t and $\overline{x}_{it}$ is the average consumption of good i at time t across all states. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

A.2.3 Non-linear Effects of Income Inequality on Expenditure Shares

Table 15: *Personal Consumption Expenditures Shares and Non-linear Inequality Effects, Durable Goods*

	log(Vehicles)	log(Furnishing)	log(Recreation)	log(Other)
Top 10%	1.502***	-0.956**	3.980***	-1.341***
	(3.07)	(-2.02)	(6.42)	(-2.60)
$(\text{Top } 10\%)^2$	-1.165**	1.151**	-3.690***	2.172***
	(-2.29)	(2.34)	(-5.73)	(4.05)
log(Income pc)	0.621***	0.724***	0.443***	-0.173***
	(18.05)	(21.82)	(10.18)	(-4.77)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.95	0.89	0.71	0.31
Observations	1,144	1,144	1,144	1,144

Note: The dependent variables are log expenditure shares of the respective consumption categories. The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data form 1997-2018. The variable Top 10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 15, Table 16, and Table 17 report the estimated effect of income inequality and income inequality squared on the log expenditure share of different subcategories of consumption goods. Note, that different to before, the coefficient of log income per capita can no longer be interpreted as an income elasticity, because the dependent variable is an expenditure share. For nearly all subcategories, income inequality seems to have a non-linear effect on the respective expenditure shares, as indicated by statistical significance of 14 out of 15 estimated coefficients of the quadratic income inequality variable.

Table 16: *Personal Consumption Expenditures Shares and Non-linear Inequality Effects, Non-durable Goods*

	log(Food)	log(Clothing)	log(Gasoline)	log(Other)
Top 10%	-0.596*	-1.582***	4.721***	1.327***
	(-1.75)	(-3.40)	(6.29)	(3.34)
$(\text{Top } 10\%)^2$	0.746**	2.398***	-4.323***	-0.888**
	(2.12)	(4.96)	(-5.55)	(-2.15)
log(Income pc)	-0.133***	-0.059*	0.020	-0.091***
	(-5.55)	(-1.81)	(0.38)	(-3.27)
Time FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
R^2	0.73	0.93	0.90	0.26
Observations	1,144	1,144	1,144	1,144

Note: The dependent variables are log expenditure shares of the respective consumption categories. The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data form 1997-2018. The variable Top 10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

Table 17: *Personal Consumption Expenditures Shares and Non-linear Inequality Effects, Service Goods*

	log(Housing)	log(Health)	log(Transport)	log(Rec.)	log(Food)	log(Insurance)	log(Other)
Top 10%	-0.747**	1.010**	-2.716***	-2.792***	-0.636*	4.081***	-2.361***
	(-2.45)	(2.46)	(-5.52)	(-4.47)	(-1.68)	(4.48)	(-5.15)
(Top 10%)^2	0.496	-1.457***	2.768***	2.665***	0.833**	-3.974***	2.298***
	(1.57)	(-3.42)	(5.41)	(4.11)	(2.12)	(-4.20)	(4.83)
log(Income pc)	-0.313***	-0.210***	0.548***	0.120***	0.232***	0.096	-0.288***
	(-14.59)	(-7.28)	(15.83)	(2.74)	(8.72)	(1.51)	(-8.95)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.33	0.82	0.78	0.19	0.55	0.23	0.43
Observations	1,144	1,144	1,144	1,144	1,144	1,144	1,144

Note: The dependent variables are log expenditure shares of the respective consumption categories. The dependent variables and income per capita are used as reported by the BEA at the US-state level, using data form 1997-2018. The variable Top 10% reports the share of income going to the top 10% of the income distribution, as reported by Mark Frank. Significance stars are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. t-statistics in parentheses.

B Theory Appendix

B.1 Savings in the Non-homothetic Model

The non-homothetic model detailed in Section 3 can be extended to encompass a savings decisions by households as well. The most straightforward way to do so is to include savings as one of the consumption goods over which the household maximizes utility. This may, for example, be driven by a preference for wealth, as proposed by, among others, Carroll (1998), Dynan *et al.* (2004), Saez and Stantcheva (2018), and Mian *et al.* (2021a).

In that case, the household optimizes the implicit utility as defined in Equation (7) over a consumption bundle (c_1, c_2, s), which now includes savings. The budget constraint is now defined over total income, rather than total expenditure, where $\mathcal{I} = p_1 c_1 + p_2 c_2 + s$ denotes total income.

$$\max_{c_1, c_2, s} \mathcal{L} = \left[(U^{\varepsilon_1} \zeta_1)^{\frac{1}{\sigma}} c_1^{\frac{\sigma-1}{\sigma}} + (U^{\varepsilon_2} \zeta_2)^{\frac{1}{\sigma}} c_2^{\frac{\sigma-1}{\sigma}} + (U^{\varepsilon_s} \zeta_s)^{\frac{1}{\sigma}} s^{\frac{\sigma-1}{\sigma}} \right] - \lambda \left[E - p_1 c_1 - p_2 c_2 - s \right]$$

Analogously to the case of consumption goods, the share of overall income used for savings is denoted by $\omega_s = (\zeta_s U^{\varepsilon_s}) \, s^{\frac{\sigma-1}{\sigma}}$.

To determine if the share allocated towards savings increases as the income level and with it utility increases, consider the following derivative:

$$\frac{\partial \frac{\omega_s}{\omega_1 + \omega_2}}{\partial U} = \frac{1}{(\omega_1 + \omega_2)^2} \cdot \frac{1}{\sigma} \cdot \omega_s \cdot U^{-1} \left[\omega_1 (\varepsilon_s - \varepsilon_1) + \omega_2 (\varepsilon_s - \varepsilon_2) \right].$$

It follows, that $(\varepsilon_s > \varepsilon_1) \cap (\varepsilon_s > \varepsilon_2)$ is a sufficient condition for the share of income devoted to saving to increase relative to the share of income devoted to consumption as the income level and with it utility increases. It is equivalent to the savings rate being convex in income and the consumption rate being concave in income. Hence if income inequality increases, high-skilled households will increase their savings by more than low-skilled households will decrease their savings, resulting in an increase in aggregate savings and a decrease in aggregate consumption.

B.2 Comparative Static

B.2.1 The Homothetic Case

The equilibrium condition is defined by the structural Equation (6)

$$F \equiv \frac{A_H H}{A_L L} - \frac{\zeta_1}{\zeta_2} p^{-\sigma} = 0.$$

The effect of an increase in A_H on p is given as

$$\frac{\partial p}{\partial A_H} = -\frac{\partial F / \partial A_H}{\partial F / \partial p}$$

The derivatives are given by

$$\frac{\partial F}{\partial p} = \sigma \frac{\zeta_1}{\zeta_2} p^{-\sigma - 1}$$

$$\frac{\partial F}{\partial A_H} = \frac{H}{A_L L}$$

Plugging in and making use of the fact that $\frac{H}{A_L L} = \frac{\zeta_1}{\zeta_2} p^{-\sigma} \frac{1}{A_H}$, it can be derived that

$$\frac{\partial p}{\partial A_H} = -\frac{p}{A_H} \frac{1}{\sigma} < 0.$$

The effect of an increase in A_H on the expenditure (which in the absence of savings is equivalent to income) of high-skilled households and low-skilled households is given by:

$$\frac{\partial E_h}{\partial A_H} = H \left(p + \frac{\partial p}{\partial A_H} \right) = H \cdot p \frac{\sigma - 1}{\sigma} < 0$$

$$\frac{\partial E_l}{\partial A_H} = 0$$

B.2.2 The Non-homothetic Case

The equilibrium in the case of non-homothetic preferences can be described by the structural equation (15), reproduced here:

$$F \equiv \frac{A_H H}{A_L L} - \frac{\zeta_1}{\zeta_2} p^{-\sigma} \frac{E_h^\sigma U_h^{1+\varepsilon_1} + E_l^\sigma U_l^{1+\varepsilon_1}}{E_h^\sigma U_h^{1+\varepsilon_2} + E_l^\sigma U_l^{1+\varepsilon_2}} = 0.$$

The effect of an increase of A_H on the equilibrium price can be calculated using the Implicit Function Theorem as

$$\frac{\partial p}{\partial A_H} = -\frac{\partial F / \partial A_H}{\partial F / \partial p}$$

Compared to the benchmark case, the comparative statics are more intricate at the demand side if preferences are non-homothetic. Specifically, the ratio of aggregate demand changes due to changes in the term

$$\frac{E_h^\sigma U_h^{1+\varepsilon_1} + E_l^\sigma U_l^{1+\varepsilon_1}}{E_h^\sigma U_h^{1+\varepsilon_2} + E_l^\sigma U_l^{1+\varepsilon_2}} = \frac{(A_H H \cdot p)^\sigma U_h^{1+\varepsilon_1} + (A_L L)^\sigma U_l^{1+\varepsilon_1}}{(A_H H \cdot p)^\sigma U_h^{1+\varepsilon_2} + (A_L L)^\sigma U_l^{1+\varepsilon_2}}.$$

$$\begin{aligned} &\partial \left(\frac{(A_H H \cdot p)^\sigma U_h^{1+\varepsilon_1} + (A_L L)^\sigma U_l^{1+\varepsilon_1}}{(A_H H \cdot p)^\sigma U_h^{1+\varepsilon_2} + (A_L L)^\sigma U_l^{1+\varepsilon_2}} \right) / \partial A_H \cdot \left((A_H H \cdot p)^\sigma U_h^{1+\varepsilon_2} + (A_L L)^\sigma U_l^{1+\varepsilon_2} \right)^2 = \\ &= \left[(A_H H \cdot p)^\sigma \left((A_H H \cdot p)^\sigma U_h^{1+\varepsilon_2} + (A_L L)^\sigma U_l^{1+\varepsilon_2} \right) U_h^{1+\varepsilon_1} \left(\frac{\sigma}{A_H} + (1+\varepsilon_1) U_h^{-1} \frac{\partial U_h}{\partial A_H} \right) \right] - \\ &- \left[(A_H H \cdot p)^\sigma \left((A_H H \cdot p)^\sigma U_h^{1+\varepsilon_1} + (A_L L)^\sigma U_l^{1+\varepsilon} \right) U_h^{1+\varepsilon_2} \left(\frac{\sigma}{A_H} + (1+\varepsilon_2) U_h^{-1} \frac{\partial U_h}{\partial A_H} \right) \right] \end{aligned} \tag{20}$$

For ease of notation, define

$$N \equiv (A_H H \cdot p)^\sigma U_h^{1+\varepsilon_2} + (A_L L)^\sigma U_l^{1+\varepsilon_2}$$
$$Z \equiv (A_H H \cdot p)^\sigma U_h^{1+\varepsilon_1} + (A_L L)^\sigma U_l^{1+\varepsilon_1}.$$

Then (20) can be rewritten as

$$\frac{\partial(Z/N)}{\partial A_H} = \frac{1}{N^2}(A_H H \cdot p)^\sigma \left[\frac{\sigma}{A_H} \left(N \cdot U_h^{1+\varepsilon_1} - Z \cdot U_h^{1+\varepsilon_2} \right) + \frac{\partial U_h}{\partial A_H} \left(N \cdot U_h^{\varepsilon_1}(1+\varepsilon_1) - Z \cdot U_h^{\varepsilon_2}(1+\varepsilon_2) \right) \right].$$

The equivalent derivative with respect to p is give by

$$\frac{\partial(Z/N)}{\partial p} = \frac{1}{N^2}(A_H H \cdot p)^\sigma \left[\frac{\sigma}{p} \left(N \cdot U_h^{1+\varepsilon_1} - Z \cdot U_h^{1+\varepsilon_2} \right) + \frac{\partial U_h}{\partial p} \left(N \cdot U_h^{\varepsilon_1}(1+\varepsilon_1) - Z \cdot U_h^{\varepsilon_2}(1+\varepsilon_2) \right) \right].$$

For ease of notation, define

$$B \equiv \left(N \cdot U_h^{1+\varepsilon_1} - Z \cdot U_h^{1+\varepsilon_2} \right)$$
$$D \equiv \left(N \cdot U_h^{\varepsilon_1}(1-\varepsilon_1) - Z \cdot U_h^{\varepsilon_2}(1+\varepsilon_2) \right)$$

Making use of N, Z, B and D, the terms of interest can be simplified to

$$\frac{\partial(Z/N)}{\partial A_H} = \frac{1}{N^2}(A_H H \cdot p)^\sigma \left[\frac{\sigma}{A_H} B + \frac{\partial U_h}{\partial A_H} D \right]$$
$$\frac{\partial(Z/N)}{\partial p} = \frac{1}{N^2}(A_H H \cdot p)^\sigma \left[\frac{\sigma}{p} B + \frac{\partial U_h}{\partial p} D \right].$$

$$\frac{\partial F}{\partial A_H} = \frac{\zeta_1}{\zeta_2} p^{-\sigma} \left(\frac{Z}{A_H} - \frac{1}{N} \right) \frac{1}{N}(A_H H \cdot p)^\sigma \left[\frac{\sigma}{A_H} B + \frac{\partial U_h}{\partial A_H} D \right]$$
$$\frac{\partial F}{\partial p} = \frac{\zeta_1}{\zeta_2} p^{-\sigma} \left(\frac{Z \cdot \sigma}{p} - \frac{1}{N} \right) \frac{1}{N}(A_H H \cdot p)^\sigma \left[\frac{\sigma}{p} B + \frac{\partial U_h}{\partial p} D \right]$$

$$\frac{\partial p}{\partial A_H} = -\frac{\partial F/\partial A_H}{\partial F/\partial p} = -\frac{\left(\frac{Z}{A_H} - \frac{1}{N} \right)}{\left(\frac{Z \cdot \sigma}{p} - \frac{1}{N} \right)} \cdot \frac{\left[\frac{\sigma}{A_H} B + \frac{\partial U_h}{\partial A_H} D \right]}{\left[\frac{\sigma}{p} B + \frac{\partial U_h}{\partial p} D \right]}$$

From this derivation it is obvious, that in general

$$\left.\frac{\partial p}{\partial A_H}\right|_{homothetic} \neq \left.\frac{\partial p}{\partial A_H}\right|_{non-homothetic}$$

It is not clear, if the effect of A_H on p is higher or lower if preferences are non-homothetic than in the homothetic benchmark case. This depends on the sign and magnitude of B and D, which in turn depend on the sign and magnitude of $\varepsilon_1 - \varepsilon_2$.