Consumption Upgrading and Wage Inequality

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Abstract

This paper examines how long-run economic growth shapes wage inequality through the joint evolution of household preferences and production technologies. I develop a unified framework that combines capital–skill complementarity with demand-side forces arising from nonhomothetic consumption behavior. Using household expenditure data linked to detailed occupation–industry information, I document two key empirical facts: (i) in the cross-section, richer households allocate a larger share of their spending to goods and services that are more skill-intensive to produce, and (ii) over time, households have increasingly shifted their expenditures toward high-skill-intensive goods over time. These patterns are consistent with prior work that has used more aggregated data. While the first suggests the potential importance of technological growth, the second fact points to nonhomothetic demand. To disentangle and quantify these two forces, I construct a multi-industry general equilibrium model featuring nonhomothetic demand, industry-specific technologies, and capital–skill complementarity. The model explains the rise in the U.S. skill premium between 1982 and 2019 through three mechanisms: an income-driven demand shift toward high-skill goods (accounting for about 5 percent of the increase), capital accumulation interacting with capital–skill complementarity (about 82 percent), and faster productivity growth in skill-intensive industries that lowers their relative prices and further amplifies demand (roughly 10 percent).

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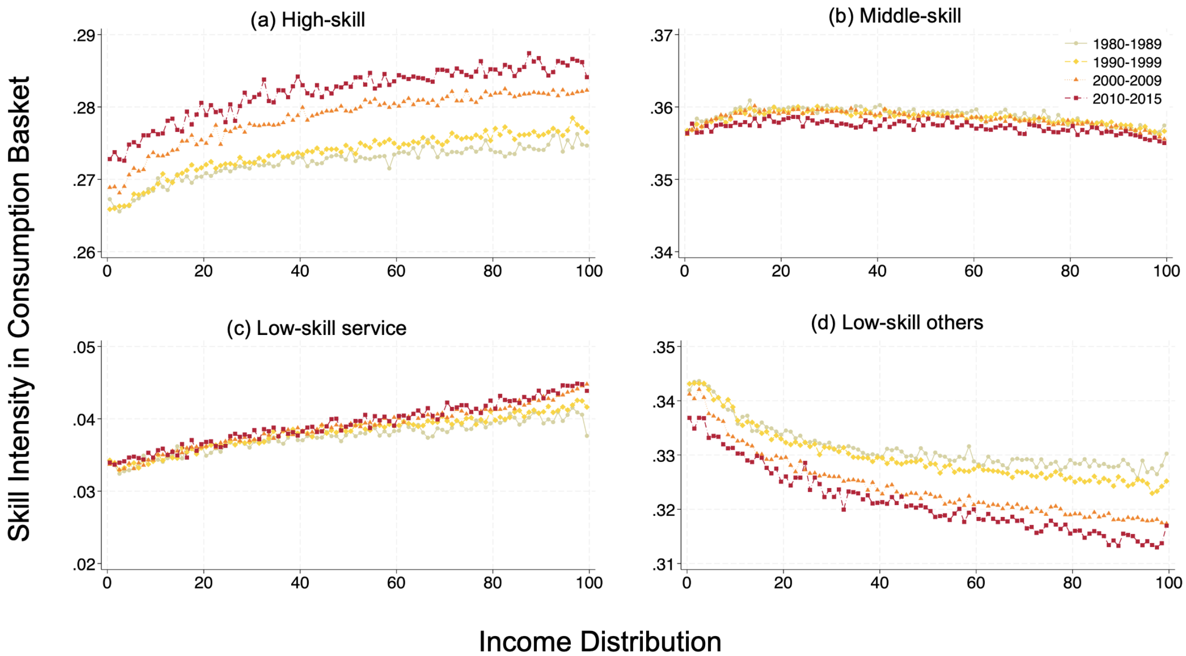
1 Introduction

Over the past few decades, there has been a secular rise in the wage gap between high- and low-skill workers in the US. A vast literature on wage inequality has focused on skill-biased technical change (SBTC) as the leading source of rising skill premiums. More recent literature has emphasized the significance of structural change on labor market outcomes. In this paper, I ask the following questions regarding the rise in wage inequality in the US: What are the sources driving the increase in skill premium? And how important are each of the factors?

I focus on a novel channel of wage inequality that operates through shifts in consumption patterns as incomes increase. I refer to this mechanism as the consumption-upgrading channel. The intuition of this channel works as follows: As I show below, household preferences are systematically associated with a shift in consumption towards skill-intensive industries when incomes grow. Consequently, any form of technological advancement that results in higher income levels will lead to an increase in demand for high-skill workers, which in turn, raises the skill premium. I incorporate the consumption-upgrading channel in a general equilibrium model through nonhomothetic preferences, and study the importance of this income-driven channel in comparison to technology-driven channels of structural change such as capital-skill complementarity and differences in productivity growth across industries.

I start by documenting a novel empirical finding regarding the changes in the skill intensity in consumption across the income distribution over time. Figure 1 shows the wage bill share of four types of labor skills purchased by households at different income percentiles. The data section describes how I construct the skill intensities in detail. By linking the household spending data from the Consumer Expenditure Survey(CEX) to good-level skill intensity data constructed using Bureau of Labor Statistics' (BLS) Occupational Employment and Wage Statistics (OEWS), O*NET and Bureau of Economic Analysis' (BEA) Detailed Input–Output (I–O) Tables, I document two sets of patterns: first, at any given time, richer households spend a higher share of their total expenditures on goods and services that require relatively more high-skill labor to produce (panel (a)). A similar pattern holds for goods and services intensive in low-skill service workers, as shown in panel (c). However, the opposite pattern holds for goods reliant on other types of low-skill workers (panel (d)): richer households spend less on goods and services that rely heavily in non-service low-skill workers. Furthermore, rich and poor households allocate similar consumption share in middle skill workers (panel (d)). These patterns imply that, holding relative prices fixed, economic growth should raise the relative demand

Figure 1: Household income percentiles and skill intensity in consumption basket



Skill intensity is calculated as the fraction of wage bill of this skill group using O*NET linked with OEWS data. The classification of each skill level is further explained in the Data section. In order to account for measurement error on individual goods and the presence of durable goods, income is imputed using education, before tax income and occupation, as in Hubmer (2023). Income percentiles are defined to be stable over time, so that households in a given income percentile bin, in any year, have the same real income.

for high-skill and low-skill service labor through an income effect, while the relative demand for other low-skill workers should experience a decline as households incomes grow.

Moreover, when examining changes over time, I find that conditional on income,[1] households have increasingly shifted their expenditures toward high-skill intensive goods and services, with the most pronounced increase occurring during the 1990s. We observe an opposite trend for goods and services relying more heavily on non-service low-skill workers, while we barely see a shift for middle-skill and low-skill service workers: the factor share of middle-skill and low-skill service workers in household consumption basket remain relative stable over time. This evolution towards high-skill intensive goods and services, and away from non-service low-skill workers likely reflects technological change, operating either through capital–skill complementarity or substitution across goods in response to changing prices.

[1]The income percentiles in figure1 are stable over time. Thus, households in a given income percentile bin have the same real income regardless of the survey year.

Motivated by these empirical findings, I formulate a general equilibrium model of structural change. The model features a nested constant elasticity of substitution (CES) production function with two worker types, capital equipment and capital structure and multiple industries. The objective is to study the sources driving the increase in the relative wage of skilled workers. The model assumes capital-skill complementarity and workers are differentiated by their substitutability with capital equipment. Industries have different productivity growth and factor intensities in production. I introduce the income-driven consumption channel by incorporating industry-specific expenditure elasticities.

In the model, growth in the stock of capital equipment is the source of SBTC due to capital-skill complementarity, thus increasing the demand for skilled labor within an industry. Increase in TFP and the stock of capital structure is skill-neutral within an industry, but affect the skill premium through shifts in consumption. First, there is a substitution effect in response to the changes in prices due to industry-specific TFP growth and factor intensities. Second, an increase in aggregate productivity growth boosts income for all households, driving consumption toward goods that are more expenditure elastic. Since these goods tend to be more skill-intensive on average, productivity growth results in an increase in the skill premium.

Next, I analyze the relative importance of the factors contributing to the rise in wage inequality, focusing on three key drivers: aggregate productivity growth, industry-specific relative productivity growth, and capital accumulation of equipments. Incorporating nonhomothetic preferences amplifies the effect of all three channels compared to a model with homothetic preferences, and thus changes their relative contributions.

Under homothetic preferences, aggregate productivity growth increases the demand for both skilled and unskilled workers proportionally, leaving relative wages unchanged. However, with nonhomothetic preferences, aggregate productivity growth generates higher demand for skilled workers through an income effect, thereby increasing the skill premium. In this context, aggregate productivity growth accounts for 5.0% of the total increase in wage inequality. Due to capital-skill complementarity, capital equipment accumulation is the dominant factor of the rising inequality, accounting for 81.8% of the total increase in the skill premium. Lastly, industry-specific productivity growth leads to a greater demand for skilled labor via a price substitution effect, contributing 9.6% to the total increase.

The remainder of the paper is structured as follows. I first provide an overview of the relevant literature. Section 2 outlines the data sources and presents empirical evidence that motivates the model. Section 3 introduces the baseline model with fixed labor supply and characterizes the equilibrium. Section 4 describes the estimation and calibration process. Section 5 presents the decomposition results and robustness checks, analyzing the roles of different driving forces in shaping the evolution of the skill premium. Additionally, I discuss the relationship between my findings and earlier results in the literature. Section 6 concludes.

1.1 Literature Review

My paper primarily contributes to the literature on the secular rise in wage inequality. It is related to two large and distinct literatures: SBTC and structural change. There is a large literature studying how SBTC has contributed to the increase in skill premium. Important early studies in SBTC emphasized that within-industry changes in skill intensity due to technology advancement is the primary driver of rising wage inequality (e.g. Katz and Murphy (1992), Bound and Johnson (1995), Berman et al. (1994)). Later papers in task routinization and capital skill-complementarity explore the micro foundation for SBTC(e.g., Autor et al. (1998), Autor et al. (2003)). While these papers also note the potential contribution of shifts in value added in the rise in skill premium, none of them systematically examine SBTC with structural change in a general equilibrium framework. Relative to them, I analyze the evolution of the skill premium within a unified framework that incorporates both SBTC as well as demand-side and production-side sources of structural change. Additionally, I emphasize the role of skill-neutral technology growth due to non-homothetic preferences, linking the increase in the skill premium to aggregate growth

This paper is also related to the literature on sources of growth and structural change. On the production side, Ngai and Pissarides (2007) emphasizes structural change driven by differences in TFP growth rates across sectors, while Acemoglu and Guerrieri (2008) studies structural change driven by capital accumulation due to industry-level differences in factor intensities Herrendorf et al. (2014) provides a survey of the structural transformation literature from the perspective of supply-side technology developments.

On the demand-side, explanations of structural change focus on shifts in consumption pattern due to income growth modeled by non-homothetic preferences. As incomes grow, demand shifts from agriculture to manufacturing and services. Earlier contributions in the demand-side explanations of structural change use Stone-Geary preferences, including Matsuyama (1992), Echevarria (1997), Kongsamut et al. (2001) and Caselli and Coleman II (2001). Recent work has explored alternative demand structures. For example, Comin et al. (2021) develops a non-homothetic CES utility function that allows for long-run income effects, thereby surpassing the limitations of traditional Stone-Geary utility functions constrained to short-term income effects. Boppart (2014) provides a unified framework of sectoral reallocation with both the income and substitution effects using non-Gorman preferences and Herrendorf et al. (2013) shows that the relative importance of the two effects to structural change depends on whether one approaches the data from a final consumption perspective or from a value-added perspective.

Relative to the structural change literature, my first contribution is the introduction of worker heterogeneity to study its effects on the skill premium. Furthermore, I consider a more disaggregated economy, organizing industries by skill intensities rather than broad sectors. I show that using detailed industry-level data is necessary for comparing different channels. Moreover, I incorporate capital-skill complementarity in my GE model with structural change, which is the leading explanation for the rise in the skill premium in the existing literature.

Three related papers that also study the income-driven channel on wage inequality are Leonardi (2015), Buera et al. (2022), and Comin et al. (2022). Leonardi (2015) observes that households with higher levels of education tend to demand more high-skill intensive services. Employing a difference-in-difference estimation approach, he concludes that the education and expenditure elasticities in favor of skill-intensive consumption items contributes to 6.5% of the increase in skill premium between 1984 and 2002. Buera et al. (2022) employ a stylized two-sector model with Stone-Geary preferences to study the impact of sector-specific TFP growth on the rise in the skill premium. They find that the sector-specific skill neutral component of technical change accounts for 18-24% of the overall increase in the skill premium between 1977 and 2005. Using a three-occupation eight-sector model, Comin et al. (2022) focus on the contribution of the income-driven channel to labor market polarization. They find that the income-driven channel accounts for 46% of changes in relative wages between low- and middle-skill workers, and 29% of the changes between high- and middle-skill workers between 1980 and 2016. Relative to these papers, I explicitly model the role of capital-skill complementarity and estimate the substitution elasticities between equipment and two skill levels. These differences result in a larger contribution for capital equipment.

In addition, my paper contributes to the literature estimating the elasticity of substitution between capital equipment and workers of different skill levels. Since the seminal work of Griliches (1969), researchers have studied how heterogeneity in substitution elasticities between capital and workers of different skill levels contributes to the rise in the wage gap. There are two standard methods for estimating the elasticity of substitution between factor inputs in production. The widely-used estimates of the substitution elasticities between capital equipment and two skill levels in Krusell et al. (2000) follow

Pseudo-maximum likelihood estimation. Using annual aggregate data from 1963 to 1993, they find the substitution elasticity between capital equipment and skilled labor to be 0.67, while the substitution elasticity between capital equipment and unskilled labor is 1.67. Other papers with more disaggregated datasets estimate the elasticity by relying on changes in relative factor prices in response to changes in factor shares. For example, Katz and Murphy (1992), Card (2009), Ottaviano and Peri (2012), Raveh and Reshef (2016) estimate the substitution elasticity between different worker types, while Karabarbounis and Neiman (2014), Raval (2019), and Hubmer (2023) estimate the substitution elasticity between capital and labor. However, it is difficult to obtain wage, cost of capital, and factor share data for the same group of goods, making direct estimates of capital-skill complementarity scarce. My estimation strategy follows Hubmer (2023) and utilizes variations in good-level exposure to long-run changes in equipment prices and wages to identify the substitution elasticity.

Finally, Jaimovich et al. (2019) studies the effect of this income channel in the context of quality upgrading within an industry. Their mechanism amplifies the effect of the consumption channel on the wage differentials.

2 Empirics

In this section, I describe the dataset used for empirical analysis and model calibration. While the traditional approach in the literature defines skill intensity based on education, I utilize a novel dataset from O*NET, which categorizes occupations into different skill levels based on job requirements, tasks and cross-sectional comparison with other occupations. I link O*NET to OEWS to compute skill intensity at the NAICS industry level. My final goal is to calculate the skill-intensity for each final consumption good recorded in the CEX, taking into account the skill intensity in production throughout its value chain. Thus, I use the BEA I-O table to adjust for skill intensity for the intermediate inputs. Table 2 shows that there is a positive correlation between expenditure elasticities and value-added skill intensities across industries.

2.1 O'Net matched OEWS Skill intensity

O'Net The Occupational Information Network (O*Net) publishes quarterly information on worker characteristics for over 950 occupations within the US economy since 2003. [2]

[2] Annual data for 1998 to 2002 is available through an extrapolated version that was evaluated and refined from existing Dictionary of Occupational Titles (DOT) data. However, researchers for longitudinal

The variable of interest in O*NET is an 8-digit occupation *Job Zone* classification. This classification provides a comprehensive measure of the vocational preparation required for each occupation. To determine the *Job Zone* for each occupation, two trained occupational experts assess various factors, including job descriptions, tasks, required levels of education, necessary work experience, on-the-job training, the position of the occupation within a career path, as well as referencing the education and training classification provided by the Bureau of Labor Statistics (BLS) (Chao & Utgoff, 2006).

In my analysis, I categorize each 6-digit Standard Occupational Classification (SOC) occupation based on the aggregate skill levels derived from the 8-digit SOC[3]: occupations with $Job\ Zone \geq 4$ are classified as high skill; occupations with $2 < Job\ Zone < 4$ are classified as middle skill; and occupations with $Job\ Zone \leq 2$ are classified as low skill[4]. I made these assignments based on the average value of *Job Zone* variable for each occupation across all available surveys.[5]. Finally, I separate low-skill service jobs from other low-skill jobs following the classification in Acemoglu and Autor (2011), since existing research suggests that low-skill service jobs have different long-term labor market trends compared with other low-skill jobs.[6]

The conventional definition of skilled workers in the academic literature typically categorizes individuals with college degrees or those employed in managerial, professional, and technical roles as skilled workers. I view my classification of skilled workers, which

studies are suggested to start from the release in April 2003(O*Net5.0).

[3]O*NET has changed its occupation codes four times in my sample period. I matched all later codes according to soc2000

[4]Definition for $job\ zone = 4$: Considerable Preparation Needed. A considerable amount of work-related skill, knowledge, or experience is needed for these occupations. For example, an accountant must complete four years of college and work for several years in accounting to be considered qualified. Most of these occupations require a four-year bachelor's degree, but some do not. Employees in these occupations usually need several years of work-related experience, on-the-job training, and/or vocational training. Many of these occupations involve coordinating, supervising, managing, or training others. Examples include real estate brokers, sales managers, database administrators, graphic designers, chemists, art directors, and cost estimators.

[5]I use O*NET 5.0 to O*NET 28.0 to maximize the number of occupations in my dataset

[6]Acemoglu and Autor (2011) broadly classify three groups of workers as service occupations: Protective Service, Food/Cleaning Service and Personal Care. The Census Bureau defines the service occupation as jobs that involve helping, caring for or assisting others. I follow their definition and classify workers who satisfy both of the following two requirements as low-skill service workers: first, ranked low-skill according to O*NET *Job Zone*, and second, belongs to one of the four major categories according to 2010 Standard Occupational Classification System from the BLS: 1) 33-0000: Protective Service Occupations; 2) 35-0000: Food Preparation and Serving Related Occupations; 3) 37-0000: Building and Grounds Cleaning and Maintenance Occupations; 4) 39-0000: Personal Care and Service Occupations. Remaining low-skill workers are mostly low-wage jobs that are concentrated in 43-0000: Office and Administrative Support Occupations; 45-0000: Farming, Fishing, and Forestry Occupations; 47-0000 : Construction and Extraction Occupations; 49-0000 : Installation, Maintenance, and Repair Occupations; 51-0000: Production Occupations; 53-0000: Transportation and Material Moving Occupations. Note that the non-service low-skill workers is a larger set than low-skill production workers.

relies on detailed occupations sourced from O*NET, to be more accurate than the standard definition for the following reasons.

First, by utilizing 6-digit occupation codes, my classification system allows for the differentiation of specific occupations based on their unique tasks and responsibilities. For instance, under my classification system utilizing *Job Zone*, Legal Assistants(23-2011) and Title Searchers(23-2093), who provide administrative and support services to legal professionals, are categorized as middle-skill workers. Despite often holding college degrees and being associated with professional occupations, their job responsibilities align more closely with administrative supporting roles. The demand for such workers has faced similar declines observed in occupations in administration and sales, who are often classified as middle skill workers. Consequently, classifying these jobs as middle-skill provides a more accurate reflection of their job functions and market demand.

Conversely, the *Job Zone* definition also places certain occupations commonly regarded as middle and low-skill into the high-skill category. For instance, Insurance Sales Agents(41-3021) are usually classified under Office and Administrative Support Occupations as middle-skill roles. However, the tasks performed by Insurance Sales Agents, including using financial analysis softwares and medical softwares to customize insurance programs to suit individual customers, are very different from the tasks performed by other occupations in sales, such as those by retail salesperson and travel agents.[7] Therefore, O*NET classify them into higher skill levels. Similarly, while most occupations in Transportation and Material Moving Occupations (53-0000) are classified as middle-skill or low-skill, Airline Pilots, Copilots, and Flight Engineers (53-2011) requires more professional skill, and are thus classified as high-skill labor.

Overall, my classification system results in a smaller number of high-skill workers compared to standard definitions based on education or broader occupational categories. Additionally, the relative wage of high-skill workers, according to my classification, is higher than the relative wage between workers with and without a college degree.

OEWS I utilize industry level occupational data from Occupational Employment and Wage Statistics (OEWS) to calculate skill intensity on the industry level. OEWS annual estimates of wage and employment data are generated using a model-based approach, drawing from responses collected in six semiannual panels spanning a three-year period. For each panel, 180,000 to 200,000 establishments are stratified within their respective states by substate area, industry, size, and ownership. When combining the sampled employment data from all six panels, OEWS encompasses a total of 83 million workers,

[7] Job description are retrieved from O*NET: `https://www.onetonline.org/link/summary/41-3021.00`.

Table 1: Skill intensity summary statistics

	High-skill	Middle-skill	Low-skill Service	Low-skill others
Employment share	17.68%	33.26%	12.59%	36.47%
Wage bill share	32.32%	36.08%	6.26%	25.35%

Notes: Skill levels are defined using *Job Zone* variable from O*NET and Acemoglu and Autor (2011). Industry-level employment and wage statistics for each occupation are retrieved from 2003 OEWS at the four-digit NAICS level. The numbers represents the fraction in the aggregate economy.

representing approximately 57 percent of the entire national workforce. I utilize the employment and wage data for each occupation within each detailed industry, using the average from both May and November surveys conducted in 2003 to match 2003 O*NET data. Moreover, this timing conveniently situates within the midpoint of my sample period.

Industry-level skill intensity I link OEWS industry employment data to O*NET occupational skill data using the 6-digit SOC to compute factor intensity of different skill levels. The factor intensity of skill $h \in \{H, M, L^s, L^o\}$ in industry i is defined as its share of total labor compensation in 2003 [8]. OEWS allows me to calculate factor intensities at selected 5-digit NAICS and most 3- and 4-digit NAICS level. I prioritize using the most granular industry level if possible, which is the 5-digit level. In cases where skill intensity at the 5-digit level is unavailable, I resort to the skill intensity at higher levels of aggregation. OEWS survey excludes the majority of the agricultural sector, so I substitute the factor intensities in these agricultural industries using sector level-factor intensities calculated using the weighted average of the limited agricultural industry level data that is available. Table 1 reports the summary statistics for employment and wage-bill shares of the four skill types.

Adjusted skill intensity using BEA I-O table. To obtain the skill intensity for final goods as measured in the CEX, I account for intermediate inputs using the 2002 BEA I-O table, following Levinson and O'Brien (2019) and Hubmer (2023)[9]. I follow the official matching to link skill intensities at the NAICS level to I-O table industry codes. Note that each I-O table industry code often corresponds to multiple NAICS codes. Consequently, I calculate a weighted average of skill intensities by considering all the matched NAICS codes, resulting in factor intensities for 417 IO industries.

[8] Wage bill is calculated using annual wage data

[9] I remove the goods and services that are missing factor intensities, since these industries are not matched with any NAICS codes, including private households and all government agencies. They accounts for a tiny portion of aggregate expenditure.

Let Θ and $\tilde{\Theta}$ denote the 417×1 vector of adjusted skill intensities and unadjusted skill intensities in each industry. Let E_N denote the 417×417 identity matrix. Let Γ denote the 417×417 commodity to commodity input-output matrix. Let H denote 417×1 vector of labor cost shares of each skill level for each commodity and let $D(z)$ denote the diagonal matrix associated with vector z. Then the adjusted skill intensity can be written as

$$\Theta = D(1-H)(\Gamma\Theta) + D(H)\tilde{\Theta} \tag{1}$$

$$\Rightarrow \Theta = \left[E_N - D(1-H)\Gamma\right]^{-1} D(H)\tilde{\Theta} \tag{2}$$

2.2 CEX consumption data

I use micro consumption data obtained from the Consumer Expenditure Survey (CEX). The CEX monitors individuals for five consecutive quarters, capturing their spending in more than 800 consumption categories categorized by UCC codes. Survey respondents are interviewed quarterly for big expenditures, such as housing, furniture and travel, while small expenditures are recorded daily by the respondents. I retrieve household-year level expenditure data from 1982 to 2016 mapped to the 2002 I-O table from Hubmer (2023). To account for business cycle fluctuations and measurement errors that are correlated with incomes(eg. under-reporting of income by richer households and over-reporting of income by poorer households commonly seen in survey data), I use the imputed permanent income to classify households into income percentiles, following Hubmer (2023).[10] I impute permanent income by regressing total expenditure on current after-tax income, education and occupation.

For each household h in year t, the final dataset from CEX consists of the value and share of expenditure in each industry, and a vector of household characteristics that includes education, after-tax income and other demographic information. Given a household's expenditure share in each industry, I calculate the factor intensity of high, middle, low-skill service, and other low-skill workers in each household's consumption basket.

I group households into income percentile bins defined consistently across years, so that households in the same percentile bin have the same real income level regardless of the survey year. For each year, I compute the average skill intensity of the household consumption basket within each income bin. I then aggregate these values by decade, taking the average across years within each decade. Figure 1 plots the resulting decade-level profiles of skill intensity in household consumption baskets across the income distribu-

[10]For example, Carroll and Dunn (1997) have found that consumption of durable goods are particularly sensitive to business cycle fluctuations. Since this paper focus on the secular rise in wage inequality, I remove the short-term business cycle fluctuations by using imputed permanent income.

tion.

2.3 Expenditure elasticities and skill intensities

Figure 2 displays the time average of expenditure elasticities against value-added skill intensities. In this analysis, aligning with the structural change literature, I use the value-added skill intensity, which is calculated as the labor share of production multiplied by the wage-bill share of high-skill workers. Thus, skill intensity reflects only high-skill workers. The marker size in the figure represents the consumption share of each category of goods. The industries with the highest skill intensity include legal services and educational institutions, while the industries exhibiting the greatest expenditure elasticity are the financial and insurance industries, as well as those associated with travel, such as hotels and air transportation.

Figure 2: Expenditure elasticities and skill intensities

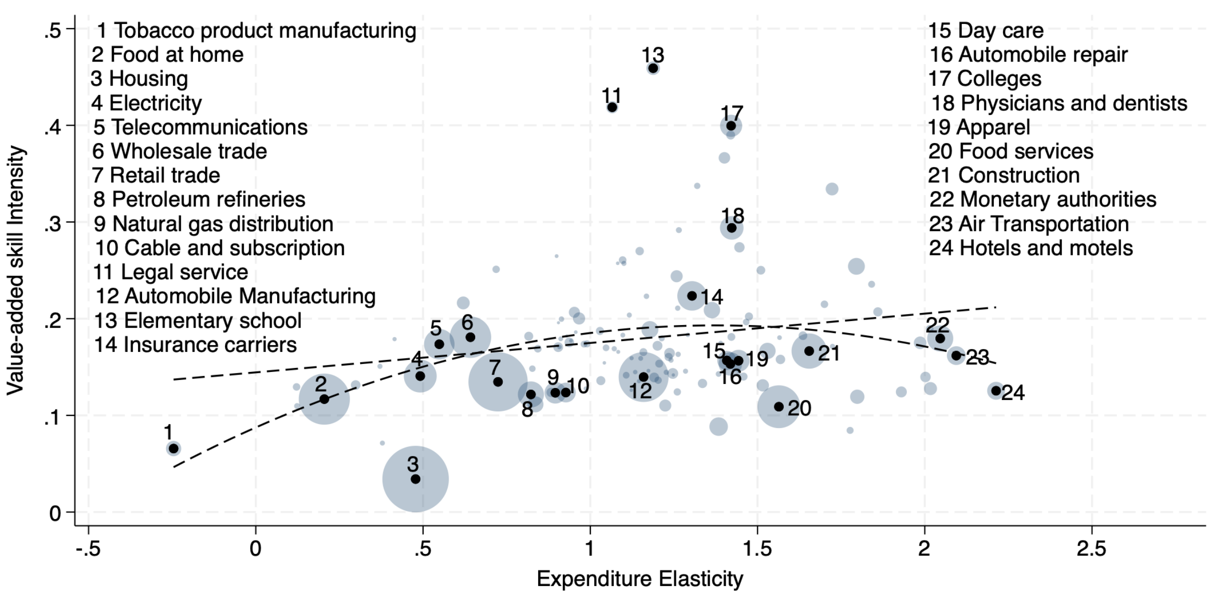


Figure 2 reports the relationship between industry-level expenditure elasticities and production skill intensities for all final goods reported in CEX. The marker size represents the consumption share. The expenditure elasticities and labor share are retrieved from the baseline estimation in Hubmer (2023), who examines a comparable disaggregated economy using CEX data. Value-added skill intensity are calculated as labor share multiplied by the wage bill share of skilled workers.

To model the relationship between expenditure elasticities and skill intensities, I apply both linear and quadratic regressions to the data. An overall positive correlation emerges between expenditure elasticities and skill intensities in production. This trend implies that an increase in income should correlate with higher consumption shares in skill-intensive good and services, consistent with the evidence presented in the top left panel in Figure 1. This finding aligns with the structural change literature as in Comin et al. (2022). [11] In addition, the quadratic regression shows a concave trend, particularly for goods with the highest expenditure elasticities which include not only skill-intensive industries but also some low-skill service industries. However, since the low-skill service industries constitutes a small consumption share, and low-skill service workers also constitute a small share of labor, these industries do not overturn the aggregate positive trends. Overall, the positive relationship between expenditure elasticities and skill intensities motivates a model with non-homothetic preferences, as discussed in the next section.

3 Model

Motivated by the empirical patterns documented above, I develop a general equilibrium model with two types of workers and two types of capital. The model incorporates non-homothetic preferences to capture the observed shifts in consumption, and explicitly features capital–skill complementarity and industry-specific productivity growth to account for technological change. Four forces drive the evolution of relative wages in this framework: aggregate productivity growth, industry-specific productivity growth, increase in the stock of capital equipment and increase in the stock of capital structure. Section 3.4 details how each of these factors contributes to the skill premium.

3.1 Production

In the market, there are I final goods operating under perfect competition. Following the capital-skill complementarity literature, I assume that the production process for each good follows a Cobb-Douglas production function with respect to capital structure (K^S), and a nested CES production function for the other inputs, including two types of labor—skilled workers (H) and unskilled workers (L)—as well as capital equipment (K^E).

There are two ways to nest K^E, H, and L within a CES production function that allow

[11] Figure 2a in Comin et al. (2022) displays a similar relationship between expenditure elasticities and log of skill intensities for eight sectors. Other than differences in the classification of skills and the level of aggregation, our treatment of skill intensity and the input-output structure is also different. I collapse the economy from the production side and the skill intensity of each final demand industries reflects the whole production chain. Comin et al. (2022) instead collapses the economy from the demand side. As a result, their value-added skill intensity across industries is more dispersed compared to mine. Herrendorf et al. (2013) discuss these two approaches to the data, which they label as the final-expenditure approach and the value-added approach. I discuss this difference in section 5.2.

for capital-skill complementarity. The first method combines K^E and L before combining their aggregate with H, restricting the elasticity of substitution between H and L to be the same as that between H and K^E. The second method combines K^E and H before combining their aggregate with L, restricting the elasticity of substitution between L and H to be the same as that between L and K^E. In both specifications, capital equipment and unskilled labor are assumed to be closer substitutes compared to capital equipment and skilled labor. The difference lies in the elasticity of substitution between labor types. In the first specification, skilled and unskilled labor complement each other, whereas in the second specification they are substitutes. Skilled labor in my data focuses on abstract tasks that are distinct from the routine tasks performed by unskilled labor. Therefore, I prefer the first modeling functional form where high- and low-skill workers are complements.[12].

The production function of industry i is given by:

$$Y_{it} = A_{it} \left(S_{it}\right)^{\beta_i} X_{it}^{1-\beta_i} \tag{3}$$

where,

$$X_{it} = \left[\alpha_i^{\frac{1}{\eta}} H_{it}^{\frac{\eta-1}{\eta}} + (1-\alpha_i)^{\frac{1}{\eta}} \left(\delta_i^{\frac{1}{\rho}} L_{it}^{\frac{\rho-1}{\rho}} + (1-\delta_i)^{\frac{1}{\rho}} (K_{it})^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{4}$$

A_{it} is factor-neutral industry-specific productivity growth. β_i, δ_i and α_i are industry-specific parameters that govern factor shares, assumed to be constant over time. η is the elasticity of substitution between capital equipment and skilled labor, and ρ is the elasticity of substitution between capital equipment and unskilled labor. Capital-skill complementarity requires $\eta < \rho$. When η and ρ approach 1, we have the standard Cobb-Douglas function. All production factors are measured in efficiency units.

Firm's problem. The representative firm in industry i takes the wages W_t^H, W_t^L and the rental rates of capital R_t^E, R_t^S as given, and maximizes its profit:

$$\underset{H_{it}, L_{it}, K_{it}^E, K_{it}^S}{Max} \; P_{it} Y_{it} - W_t^H H_{it} - W_t^L L_{it} - R_t^E K_{it}^E - R_t^S K_{it}^S \tag{5}$$

Then from the firm's optimization condition, the final good price in industry i can be

[12]See Krusell et al. (2000) and Parro (2013) for discussion on the second specification

written as

$$P_{it} = \frac{1}{A_{it}} \left(\frac{R_t^S}{\beta_i} \right)^{\beta_i} \left(\frac{P_{it}^X}{1 - \beta_i} \right)^{1-\beta_i} \tag{6}$$

where P_{it}^X denotes the factor price of X_{it}, and can be written as

$$P_{it}^X = \left[\alpha_i \left(W_t^H \right)^{1-\eta} + (1-\alpha_i) \left[\delta_i \left(W_t^L \right)^{1-\rho} + (1-\delta_i) \left(R_t^E \right)^{1-\rho} \right]^{\frac{1-\eta}{1-\rho}} \right]^{\frac{1}{1-\eta}} \tag{7}$$

Equation 6 indicates that higher industry-level productivity growth and lower cost of production factors lead to lower prices for the final good. Suppose there is an exogenous drop in the cost of capital equipment while holding wages constant, industries that are intensive in capital equipment would experience a larger drop in final prices. On the other hand, when considering the GE effects on wages, as the cost of capital equipment decreases, labor demand for low-skill workers decrease as production shifts towards equipments, while demand for high-skill workers increases since they complements equipments.

3.2 Demand

Each worker is endowed with capital $\bar{K^S}$ and $\bar{K^E}$ and one unit of labor. To focus on the channel of shifts in consumption, this model abstracts from investment and assumes that the return on capital is equally distributed across all households.

A fraction f of the population are high skilled and $1 - f$ are low skilled. I assume a log demand function that can be implied by some underlying primitive utility function.[13]. All Consumers have the same preference. Thus, they share the same compensated substitution elasticity σ, and the same good-specific elasticity of substitution γ_{it}. The only difference in their expenditure shares comes from differences in income at any given point in time. The expenditure share of good i for household h is $\omega_{it}^h = \frac{C_{it}^h P_{it}}{E_{it}^h}$, where this share is exogenously given in the initial period and evolves over time according to

[13]Log-demand offers the advantage of flexibility in modeling income effects. Examples using log-demand include Goos et al. (2014) for homothetic preferences and Hubmer (2023) for non-homothetic preferences.

$$d\ln\omega_{it}^{h} = (1-\sigma)d\ln\frac{P_{it}}{P_t^h} + (\gamma_{it}-1)d\ln\frac{E_t^h}{P_t^h}, \quad h \in \{H, L\} \tag{8}$$

where the change in household-level income and aggregate price index are given by:

$$E_t^h = W_t^h + R_t^E \bar{K}_t^E + R_t^S \bar{K}_t^S \tag{9}$$

$$d\ln P_t^h = \sum_i \omega_{it}^h d\ln P_{it} \tag{10}$$

Equation 8 illustrates that the reallocation in consumption across industries is driven by changes in the relative prices of goods and changes in total expenditure. In a model with homothetic preferences, the expenditure elasticity γ_{it} equals to one for all industries at all times. Thus, the substitution effect driven by changes in relative prices from the production side are the only source of industry reallocation. Consumption shifts into industries with higher productivity growth and larger drops in the cost of production. In a model with non-homothetic preferences, however, households also shift their consumption towards industries with higher expenditure elasticities as total expenditures increase. Industries with $\gamma_{it} > 1$ are luxury goods whose expenditure shares increase with total expenditure, while industries with $\gamma_{it} < 1$ are necessity goods whose expenditure shares decrease with total expenditure[14].

3.3 Equilibrium

I normalize the wage for low-skill workers to be one. Solving for equilibrium requires us to find the rental rates of capital (R_t^E, R_t^S), and the wage premium W_t^H, such that given the factor prices and the implied goods prices, all factor and goods markets clear.

More specifically, the competitive equilibrium consists of the factor prices $\{R_t^S, R_t^E, W_t^H\}$, goods prices $\{P_{it}\}_{i\in I}$, consumer demand for all industries $\{C_{it}^H, C_{it}^L\}_{i\in I}$, total expenditure for both labor types $\{E_t^H, E_t^L\}$, final good outputs $\{Y_{it}\}_{i\in I}$ and factor input choices $\{H_{it}, L_{it}, K_{it}^E, K_{it}^S\}_{i\in I}$, such that:

1. Consumer demand is given by $C_{it} = \frac{\omega_{it}E_t}{P_{it}}$, where ω_{it} is endogenously given at $t = 0$ and evolves according to equation 8;

2. Given goods prices, $\{P_{it}\}_{i\in I}$ and factor prices, W_t^H, R_t^E, R_t^S, final good output $\{Y_{it}\}_{i\in I}$

[14] I follow Hubmer (2023) and use time-varying industry-level expenditure elasticities, but estimation shows that they are very stable over time. Please refer to section 5.3 in Hubmer (2023) for more details.

and factor input choices $\{H_{it}, L_{it}, K^E_{it}, K^S_{it}\}_{i\in I}$ are consistent with profit maximization subject to equation 3;

3. All final goods markets clear, $fC^H_{it} + (1-f)C^L_{it} = Y_{it}$;

4. All factor markets clear, $f = \sum_{i\in I} h_{it}$, $(1-f) = \sum_{i\in I} l_{it}$, $\bar{K^E_t} = \sum_{i\in I} K^E_{it}$, $\bar{K^S_t} = \sum_{i\in I} K^S_{it}$.

3.4 Mechanism

Four forces drive the evolution of relative wages in this framework: aggregate productivity growth, industry-specific productivity growth, growth in the stock of capital equipment, and growth in the stock of capital structures. I now explain how each of these factors raises the relative wage of high-skill workers.

First, aggregate productivity growth (A_t) and the expansion of capital structures (S_t) affect the skill premium primarily through an income effect. Both are skill-neutral within each industry. However, because preferences are non-homothetic, they shift the composition of final demand across industries. When industries with higher expenditure elasticities are also more skill intensive ($Cov(\alpha_i, \gamma_i) > 0$), income growth driven by A_t and S_t raises demand for skilled labor, thereby increasing the skill premium. Figure 2 documents this positive correlation between industry-level expenditure elasticities and skill intensity.

Second, growth in the stock of capital equipment raises the skill premium through capital–skill complementarity. The data show both a sharp decline in the relative price of equipment and a substantial increase in its stock.[15] When equipment capital substitutes for low-skill workers but complements high-skill workers, capital deepening in equipment shifts relative demand toward skilled labor, raising their relative wage. Unlike the income effect, this operates within industries. In the quantitative analysis below, I estimate the elasticity of substitution between equipment and each type of labor, finding $\rho > 1 > \eta$, consistent with capital–skill complementarity.

Third, industry-specific productivity growth (A_{it}) influences the skill premium through a price effect. Industries experiencing faster productivity growth see larger price declines. Since final goods are substitutes across industries ($\sigma > 1$), demand shifts toward these faster-growing sectors. If such industries are relatively skill intensive, this reallocation raises the relative wage of skilled labor. Figure 4a shows that calibrated industry-level productivity growth is positively correlated with industry skill intensity.

[15] I take as given the exogenous increase in the stock of capital equipment observed in the data. This may itself be driven by investment-specific productivity improvements.

Finally, industry-specific productivity growth also reinforces capital–skill complementarity. If faster-growing industries are more equipment intensive, then their relative productivity growth further increase the demand for capital equipment in these industries. This in turn boosts demand for skilled labor, as equipment accumulation disproportionately complements high-skill workers. Figure 4b confirms that industry-level productivity growth is positively correlated with factor shares of equipment.

4 Estimation and Calibration

To quantify the impact of various channels within the model, I first estimate or calibrate the model parameters. These include the preference parameters $\{\gamma_{it}, \sigma\}_{i\in I, t\in[1982,2012]}$, technology parameters $\{\beta_i, \alpha_i, \delta_i, \eta, \rho, A_{it}, A_t^H, A_t^{K^E}, A_t^{K^S}\}_{i\in I}$, and consumption shares at the initial steady state for both types of labor $\{\omega_{it}^H, \omega_{it}^L\}_{i\in I, t=1982}$, the stocks of capital structures and capital equipment $\{k_{it}^S, k_{it}^E\}_{t\in[1982,2012]}$, and the fraction of high-skill workers in the economy f.

The sources and summary statistics for these parameters are reported in table 2. I begin with estimating the two parameters for capital-skill elasticity of substitutions, followed by a description of the calibration process for the remaining parameters. I use the demand-side elasticities estimated by Hubmer (2023). Finally, I isolate each of the channel and study their individual contribution to the rise in skill premium.

Table 2: Calibration

Parameter	Moment/Description	Value[a]	Sources
ρ	Elasticity of substitution between K^E and L	1.31	My estimation
η	Elasticity of substitution between H and K^E	0.46	My estimation
γ_{it}	Expenditure elasticity for Y_i	1.0	Hubmer (2023)
σ	Elasticity of substitution between goods	1.55	Hubmer (2023)
$\omega_{i,1982}^H$[b]	Initial consumption share of Y_i for H workers		Data(CEX)
$\omega_{i,1982}^L$	Initial consumption share of Y_i for L workers		Data(CEX)
δ_i	governs L share in production in 2003	0.71	Data(IO+OEWS+ONET)
α_i	governs H share in production in 2003	0.20	Data(IO+OEWS+ONET)
β_i	governs K^S share in production in 2003	0.19	Data(IO+OEWS+ONET)
f	Share of H workers in 2003	0.25	Data(OEWS+ONET)

[a] I report the time-average of consumption weighted mean for δ_i, α_i, β_i, and γ_{it}
[b] calculated using consumption of top 30% HHs

4.1 Estimation of capital-skill complementarity

The estimation of the capital-labor elasticity of substitution relies on the variation of industry-level exposure to the secular change in capital equipment prices and wages. My method of using long-run changes in rental rates and factor shares to estimate the elasticities of substitution between capital and labor builds on Karabarbounis and Neiman (2014), Raval (2019) and Hubmer (2023).

My estimation focuses on long-run trends, taking into account the reorganization of the production process and the reallocation of tasks between skill levels and between labor and equipment. This strategy may generate different results compared to estimations using high-frequency cross-sectional data. I measure the percentage change in all variables using annual data from 2002 to 2018.[16] I replace the variables in levels with their average value in the sample and interpret the regression as representing changes from an initial to a final steady state.

My regression data is based on final demand industries, while the factor shares in production account for all intermediate inputs throughout the value chain. This method is labeled as the *final expenditure approach* in Herrendorf et al. (2013), in constrast to the *value-added approach*. Consequently, my elasticities capture not only changes in the production process within an industry but also changes across intermediate inputs.

My estimation strategy utilizes the changes in factor shares. It is reasonable to assume that all factors are measured in efficiency units. Let $H_{it} = A^H_{it} h_{it}$, $L_{it} = A^L_{it} l_{it}$, $K^E_{it} = A^E_t k^E_{it}$ and $K^S_{it} = A^S_{it} k^S_{it}$, where A^H_{it}, A^L_{it}, A^E_{it} and A^S_{it} are factor-augmenting technologies, and h_{it}, l_{it}, k^E_{it} and k^S_{it} are the factor inputs. The first order conditions in the firm's profit maximization problem imply the following relationships for the value-added factor shares θ_{it} for the four factor inputs:

$$\theta^S_{it} = \frac{R^S_t k^S_{it}}{P_{it} Y_{it}} = \beta_i \tag{11}$$

$$\theta^H_{it} = \frac{W^H_t h_{it}}{P_{it} Y_{it}} = \frac{\alpha_i}{1-\alpha_i} \left(\frac{P^M_{it}}{W^H_t / A^H_{it}} \right)^{\eta - 1} \theta^M_{it} \tag{12}$$

[16] This sample period is constrained by the OEWS data. The first year using NAICS industry classification is 2002. More details about the data construction are discussed in the appendix.

$$\theta^L_{it} = \frac{W^L_t l_{it}}{P_{it}Y_{it}} = \delta_i \left(\frac{P^M_{it}}{W^L_t / A^L_{it}} \right)^{\rho-1} \theta^M_{it} \tag{13}$$

$$\theta^E_{it} = \frac{R^E_t k^E_{it}}{P_{it}Y_{it}} = (1-\delta_i) \left(\frac{P^M_{it}}{R^E_t / A^E_{it}} \right)^{\rho-1} \theta^M_{it} \tag{14}$$

where $\theta^M_{it} = \frac{P^M_{it} M_{it}}{P_{it}Y_{it}} = (1-\alpha_i)(1-\beta_i) \left(\frac{P^X_{it}}{P^M_{it}} \right)^{\eta-1}$. Note that $\theta^S_{it} + \theta^E_{it} + \theta^H_{it} + \theta^L_{it} = 1$ and $\theta^E_{it} + \theta^L_{it} = \theta^M_{it}$.

4.1.1 Estimation of $\rho - \eta$

Using the relative skill intensities, I start with estimating the difference between the elasticity of substitution of capital equipment and two labor types: $\rho - \eta$. Log-linearizing the ratio of equation 13 and 12, I get

$$ln \left(\frac{\theta^L_{it}}{\theta^H_{it}} \right) = ln \left(\frac{\alpha_i}{(1-\alpha_i)\delta_i} \right) + (\rho - \eta) ln(P^M_{it}) + (\eta - 1) ln \left(\frac{W^H_t}{A^H_{it}} \right) + (1-\rho) ln \left(\frac{W^L_t}{A^L_{it}} \right) \tag{15}$$

This equation says that in the presence of capital-skill complementarity ($\eta < \rho$), a decrease in the combined cost of unskilled labor and capital equipment (p^M_{it}), in efficiency units, leads to an increase in the relative skill intensity in production (measured as the wage bill share of skilled labor). In the data, changes in p^M_{it} are largely driven by the decrease in equipment prices, which is more than 10 times larger than the change in wage of unskilled labor. Rewriting equation **??** in changes between two arbitrary periods gives

$$\hat{p}^M_{it} = \frac{\theta^L_i}{\theta^M_i} (\hat{w}^L_t - \hat{a}^L_{it}) + \frac{\theta^E_i}{\theta^M_i} (\hat{r}^E_t - \hat{a}^E_{it}) \tag{16}$$

where $\hat{Z} = lnZ_{t'} - lnZ_t$ indicates the percentage change of variable Z between period t and t'. Plugging equation 16 back into equation 15 and adding industry and time fixed effects gives the following estimation equation:

$$ln\frac{\theta^L_{it}}{\theta^H_{it}} = \tilde{\alpha}_i + \lambda_t + (\rho-\eta)\left[\frac{\theta^L_i}{\theta^M_i}\hat{w}^L_t + \frac{\theta^E_i}{\theta^M_i}\hat{r}^E_t\right] + \underbrace{\xi_{it}}_{-(\rho-\eta)\left[\frac{\theta^L_i}{\theta^M_i}a^L_{it}+\frac{\theta^E_i}{\theta^M_i}a^E_{it}\right]-(\eta-1)a^H_{it}-(1-\rho)a^L_{it}} \tag{17}$$

The time fixed-effect λ_t absorbs the wage growth as well as all common trends outside the model, including uniformly rising markups and time-specific measurement error. All factor-augmenting technology progress is captured in the error term. When skill-augmenting technology progress is orthogonal to the factor shares θ^M_i and θ^E_i, then $\rho-\eta$ are identified. However, variation in TFP is largely unobservable. In practice, the growth in the technology terms are too small relative to the change in p^M_{it} to create large bias in the estimates.

Table 3: Estimates of $(\rho-\eta)$

	2002-2018 PERIC (1)	**2002-2011 PERIC** (2)	**2002-2011 PERICD** (3)
$\rho-\eta$	0.811**	0.861***	1.141***
	(0.015)	(0.003)	(0.003)
N	2128	1197	1197

Note: All columns weigh goods by final demand shares. Time and good fixed effects are used in all specifications. Standard errors, in parentheses, are clustered at the good level. Wage bill share is calculated from OEWS-ONET as described in section 2. Equipment intensities and labor shares are taken from the baseline estimation in Hubmer (2023). Column 1-2 use the relative prices for equipment from (FRED series: PERIC) to calculate changes in equipment prices, and column 3 uses the relative prices for equipment and softwares (FRED series: PERICD, available until 2011).

Table 3 shows the estimates of capital-skill complementarity $\rho-\eta$ using equation 17. The changes in wage bill share and changes in wages are calculated from OEWS-O*NET.[17] I use U.S. data from 2002 to 2018 to estimate the elasticities.[18] Assuming a constant household discount factor and capital depreciation rate, changes across steady states in the rental rate of capital only reflect changes in the relative price of capital equipment. I use the annual average from two time series for the equipment prices. $PERIC$ reflects changes in equipment prices and $PERICD$ reflects changes in prices for both software and equipment. Since $PERICD$ is only available until 2011, I redo the analysis using $PERIC$ for

[17]Please see the appendix for more detailed descriptions of construcion of the data used in the estimation.

[18]This sample period is restricted by OEWS data using NAICS industry classification, which starts at 2002.

2002 to 2011 for a robustness check.

All estimates have positive statistically significant results, implying capital-skill complementarity. My preferred estimate of $\rho - \eta$ is 0.81 because it covers the whole sample.

4.1.2 Estimation of $\eta - 1$

The estimation of $\eta - 1$ is based on the factor share of skilled labor only. Plugging θ_{it}^{M} into equation 12 and taking logs, I get

$$ln(\theta_{it}^{H}) = ln\left(\alpha_i(1-\beta_i)\right) + (\eta-1)ln(P_{it}^{X}) - (\eta-1)(ln(W_t^{H}) - ln(A_{it}^{H})) \tag{18}$$

This equation says that if capital equipment and skilled labor are complements ($\eta < 1$), then a decrease(increase) in the total cost of labor and capital equipment P_{it}^{X} leads to an increase(decrease) in the production intensity of skilled labor. Rewriting equation 7 in changes between two arbitrary periods and plugging in $\hat{p}_{it}^{M}$ gives

$$\begin{aligned}\hat{p}_{it}^{X} &= \frac{\theta_i^{H}}{\theta_i^{M}+\theta_i^{H}}(\hat{w}_t^{H} - a_{it}^{H}) + \frac{\theta_i^{M}}{\theta_i^{M}+\theta_i^{H}}\hat{p}_{it}^{M} \\ &= \frac{\theta_i^{H}}{1-\beta_i}(\hat{w}_t^{H} - a_{it}^{H}) + \frac{\theta_i^{L}}{1-\beta_i}(\hat{w}_t^{L} - \hat{a}_{it}^{L}) + \frac{\theta_i^{E}}{1-\beta_i}(\hat{r}_t^{E} - \hat{a}_{it}^{E})\end{aligned} \tag{19}$$

Thus, the estimation equation becomes

$$\begin{aligned}ln(\theta_{it}^{H}) = \tilde{\alpha}_i + \lambda_t + (\eta-1)&\left[\frac{\theta_i^{H}}{1-\beta_i}\hat{w}_t^{H} + \frac{\theta_i^{E}}{1-\beta_i}\hat{r}_t^{E} + \frac{\theta_i^{L}}{1-\beta_i}\hat{w}_t^{L}\right] \\ &+ \overbrace{-(\eta-1)\left[\frac{\theta_i^{H}}{1-\beta_i}a_{it}^{H} + \frac{\theta_i^{E}}{\beta_i-1}a_{it}^{E} + \frac{\theta^{L}}{1-\beta_i}a_{it}^{L}\right] + (\eta-1)a_{it}^{H}}^{\xi_{it}}\end{aligned} \tag{20}$$

Table 4 shows the estimates of the elasticity of substitution between capital equipment K^E and skilled labor H. The changes in factor share of skilled labor is calculated as the industry-level wage bill share from OEWS-O*NET multiplied by the industry-level labor share averaged across 2002 to 2012 retrieved from Hubmer (2023). The OLS estimates range from -0.29 to -0.71. My preferred estimates is -0.55, which lies in the middle of the range and implies an elasiticity of substitution between skilled labor and capital equipment of 0.45. Taking the preferred estimates of $\rho - \eta$ from above, then the elasticity of substitution between unskilled labor and capital equipment is 1.26.

Table 4: Estimates of $(\eta - 1)$

	2002-2018 PERIC (1)	**2002-2011 PERIC** (2)	**2002-2011 PERICD** (3)
$\eta - 1$	-0.544*	-0.545**	-0.706*
	(0.056)	(0.049)	(0.056)
N	2128	1197	1197

Note: All columns weigh goods by final demand shares. Time and good fixed effects are used in all specifications. Standard errors, in parentheses, are clustered at the good level. Factor share of skilled labor is calculated as the wage bill share from OEWS-O*NET multiplied by the industry-level labor share taking from Hubmer (2023), which is available until 2012. I use the average of labor share from 2002 to 2012 to increase the sample size and to focus on the variation in skill intensity. Equipment intensities and labor shares are taken from the baseline estimation in Hubmer (2023). Column 1-2 and 4-5 use the relative prices for equipment from (FRED series: PERIC) to calculate changes in equipment prices, and column 3 and 6 uses the relative prices for equipment and software (FRED series: PERICD, available until 2011).

4.1.3 Comparison with the prior literature

Despite the large literature estimating the elasticity of substitution between labor types(eg. Card (2009) Ottaviano and Peri (2012), Raveh and Reshef (2016)) and between capital and labor (eg. Chirinko (2008), Karabarbounis and Neiman (2014), Oberfield and Raval (2021)), estimates of the substitution elasticity between capital and labor by skill level remain scarce. This is primarily due to the difficulty in simultaneously obtaining changes in factor shares and changes in capital returns and wages by skill level for the same group of goods.

A widely cited study providing estimates of the substitution elasticity between capital and two skill levels is Krusell et al. (2000). They estimate these substitution elasticities, along with factor-augmenting technology growth and parameters governing factor shares, using a two-step simulated method of moments applied to annual country-level data from 1963 to 2002. Their findings indicate that the substitution elasticity between skilled labor and capital is 0.67, while for unskilled labor and capital is 1.67. My results of 0.45 and 1.26 confirm their findings that capital substitutes for unskilled labor and complements skilled labor. My smaller estimates for both of the elasticities would imply a higher degree of complementarity between capital equipment and both types of labor. Thus, the same exogenous increase in capital stock would generate higher growth in wages. In the quantitative exercises, I also include decomposition exercises using the estimates from Krusell et al. (2000) as robustness checks.

Karabarbounis and Neiman (2014) also estimate the long-run elasticity by leveraging variation in the relative price of equipment, similar to my approach. However, while I use the differential exposures across final demand industries to the secular decline in equipment prices, they use the differential exposure across countries. Although their paper primarily focuses on the capital-labor elasticity of substitution, they also consider changing skill composition in their robustness checks. Using a nested CES function, their estimate of the substitution elasticity between unskilled labor and capital ranges from 1.19 to 1.34. My estimate of 1.26 falls within this range. Unfortunately, they do not estimate the elasticity of substitution between skilled labor and equipment.

4.2 Remaining parameters

The expenditure elasticities γ_{it} and price elasticity σ are adopted directly from the estimation conducted by Hubmer (2023) using cross-sectional CEX data. I allow good-level expenditure elasticities to vary over time, but the variation is very small. The initial expenditure share for industry i for high-skill workers, denoted as $\omega^H_{i,2002}$, is computed using the mean of the top 30% of households in the CEX, while $\omega^L_{i,2002}$ is defined as the mean expenditure share of the remaining households. The fraction of high-skill workers, denoted as f, is determined by the fraction of high-skill workers employed in 2003 calculated using OEWS-O*NET data.

I calibrate the industry-level production parameters β_i, α_i and δ_i to match the factor shares in 2003. The model assumes β_i, α_i and δ_i to be constant over time, and that changes in factor shares over time are driven by an exogenous increase in capital equipment ΔK^E_t due to capital-skill complementarity.

The remaining model parameters are the factor neutral productivity series A_{it}, and the evolution in capital stock for equipment and structures K^E_t, K^S_t. The stock of capital evolves according to the data. capital equipment K^E includes equipment and machinery as well as intangible assets such as software(FRED series: K1NTOTL1EQ000). capital structure K^S accumulates the cost of construction activity such as overhead and office costs, as well as the cost of materials and engineering, but does not include the cost of residential buildings(FRED series: K1NTOTL1ST000) (Lally (2009)). Note that in the model, an increase in the capital stock is isomorphic to increasing the capital-augmenting technology.

The residual part of growth can be attributed to TFP. Figure 3a compares my calibrated

TFP growth with the TFP series estimated by the BLS (FRED series: MFPPBS). I first calibrate a common TFP growth series for all industries (A_t), targeting the trend of real per capita GDP (FRED series: A939RX0Q048SBEA).[19] Alternatively, I also incorporates industry-specific productivity growth. I use changes in relative prices across industries to calibrate the ratio of productivity growth between industries, capturing industry-specific variation in A_{it}, while jointly matching real per capita GDP.[20] In a model with identical CES production functions across industries, changes in relative prices correspond inversely to changes in industry-level productivity growth. In my model, which allows for variation in factor intensities, the relative prices and industry-level productivity growth are linked through equation 6, where the factor prices also play important roles. The appendix provides the calibrated industry-level productivity growth for all 133 industries averaged over time. The fastest-growing industries include advanced manufacturing sectors reliant on information and technology, such as measuring and computing device manufacturing, and electronic computer manufacturing.

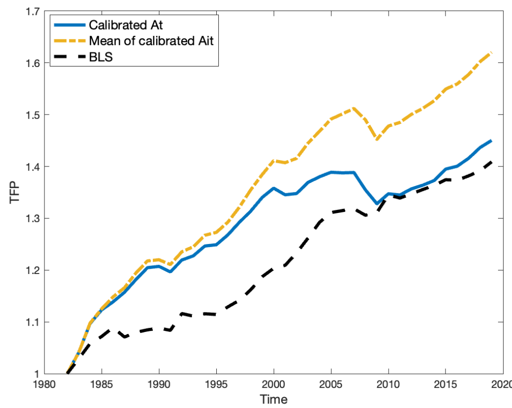
Figure 3a plots the trend in aggregate TFP growth implied by my calibration alongside the TFP series reported by the BLS. I present two model-based series: aggregate TFP growth in a specification without industry-specific productivity growth, and the value-added weighted average of industry-level productivity growth in a specification that allows for heterogeneous productivity growth across industries. Both of which matches growth in real per capita GDP. In the quantitative analysis that follows, I use three alternative measures of TFP growth: calibrated aggregate component of TFP A_t, calibrated industry-specific TFP A_{it}^{GDP} (with heterogeneous productivity growth), and industry-specific TFP $A^{BLS}it$ (aligned with the BLS series and relative price changes)

In figure 4a and 4b, I present the relationship between the calibrated industry-specific TFP growth rates ΔA_{it} and the factor intensities of high-skill workers and capital equipment in each industry. There is a positive correlation between industry-specific TFP growth and industry-level skill intensity, suggesting faster growth in the skill-intensive industries during this period. Moreover, there is also a weak positive correlation between ΔA_{it} and K_{it}^{E}, indicating a positive interaction effect on the skill premium from the relative growth across industries and capital accumulation.

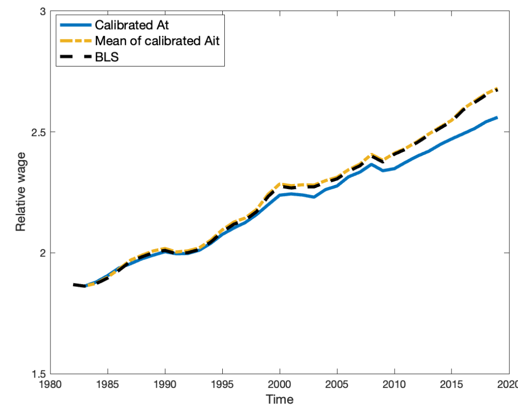
[19] In both the model and data, real per capita GDP is calculated using the Fisher Chained Price Index.

[20] Industry-level prices are obtained from Hubmer's replication kit and are derived from annual chained-price indices for gross output at the summary level for 71 industries.

Figure 3: Model predictions

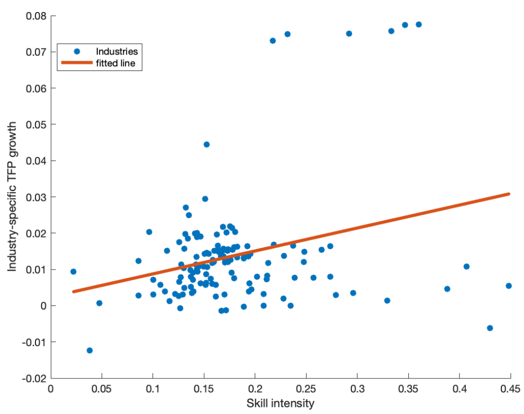


(a) TFP

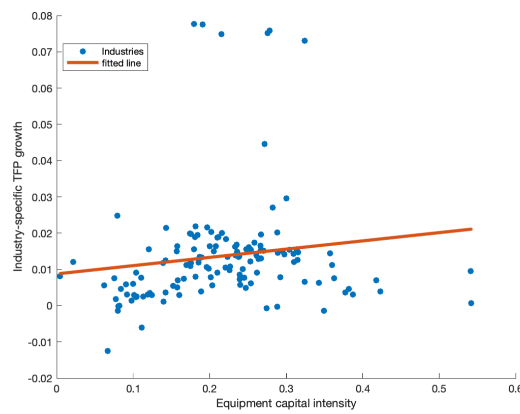


(b) W^H

Figure 4: Correlation between TFP growth and factor intensities



(a) $Corr(\Delta A_{it}, \theta_i^H) = 0.288$



(b) $Corr(\Delta A_{it}, \theta_i^{K^E}) = 0.137$

ΔA_{it} is the productivity growth averaged over time for each industry i, where A_{it} is calibrated from the model. Skill intensities are calculated from OEWS-O*NET and capital equipment intensities are retrieved from Hubmer (2023). The fastest growing industries are: 1) other measuring and controlling device manufacturing, 2) electronic computer manufacturing, 3) other communications equipment manufacturing, 4) telephone apparatus manufacturing, 5) audio and video equipment manufacturing and magnetic, and 6) optical recoding media manufacturing. These industries exceed average TFP growth by almost four times. In the appendix, I show the time-average of industry-level TFP growth for all 133 industries.

5 Quantitative analysis

In this section, I analyze the impact of incorporating nonhomothetic preferences on changes in wage inequality, finding that it leads to a greater increase in relative wages compared to a model with homothetic preferences. I then investigate the channels through which con-

Table 5: Model Comparison.

	Homothetic ($\gamma_{it} = 1$)			Nonhomothetic		
	(1)	(2)	(3)	(4)	(5)	(6)
	A_t	A_{it}^{GDP}	A_{it}^{BLS}	A_t	A_{it}^{GDP}	A_{it}^{BLS}
ΔW_t^H	34.8%	40.2%	40.2%	37.0%	43.5%	43.2%

Notes: This table compares the increase in wage inequality across models with and without nonhomothetic preferences, using three alternative measures of productivity growth. Columns (1) and (3) report results based on productivity growth calibrated to match per capita GDP growth (FRED series: A939RX0Q048SBEA), assuming uniform growth across all industries. Columns (2) and (4) incorporate industry-specific productivity growth by adjusting for changes in relative prices over the sample period, while still matching per capita GDP growth. Columns (3) and (6) further match both the change in relative prices and industry-level TFP growth from the BLS (FRED series: MFPPBS).

sumption upgrading amplifies the rise in the skill premium. Using the calibrated model and parameter values, I conduct a counterfactual analysis to assess the contribution of three key factors to the increase in the skill premium: 1) skill-neutral TFP growth (A_t) and capital accumulation in structures (S_t), 2) capital accumulation in equipment (K_t), and 3) industry-specific relative TFP growth (A_{it}). Finally, I compare my findings with previous results from the literature.

5.1 Sources of rising skill premium

In my baseline model with the calibrated industry-specific TFP growth matching per capita GDP growth (A_{it}^{GDP}), I predict a 43.5% increase in the relative wage of skilled workers from 1.87 to 2.68 from 1982 to 2019.[21] In Figure 3b, I show the evolution of the relative wage during the sample period using three TFP series discussed earlier. Using only the aggregate TFP growth generates a slightly smaller increase in the relative wage, while using the industry-specific TFP matching the BLS series generates almost the same increase.

Ignoring consumption upgrading leads to an underestimation of the increase in wage inequality. Table 5 compares the rise in relative wages between a homothetic and a nonhomothetic model. Incorporating nonhomothetic preferences amplifies the increase in relative wages across all scenarios. This amplification effect operates through productivity growth and capital accumulation of equipment and structures. Table 6 separately study the contribution of these factors to the rising skill premium. For robustness check, Table 8 in Appendix B presents results from the same counterfactual analysis using TFP

[21] In comparison, Buera et al. (2022) documents that the skill premium increased by 41.5% from 1982 to 2005 using World KLEMS data; Comin et al. (2022) documents a 27.7% from 1977 to 2005 using CPS.

series from the BLS.

I start with feeding in the aggregate TFP growth (ΔA_t) and the increase in capital structure (ΔS_t), while holding capital equipment (K_t) and the industry-specific component of the TFP growth constant (A_{it}). In a standard model with homothetic preference, skill-neutral technology growth have virtually no effect on the relative wage.[22] However, in a model with nonhomothetic preferences, changes in A_t and S_t generate an income effect that shifts consumption towards more expenditure-elastic industries. This shift is biased towards skilled labor, as skill-intensive goods are, on average, more expenditure-elastic. In the nonhomothetic model, aggregate productivity growth results in a 2.2% increase in the relative wages of skilled workers, contributing to 5.0% of the total increase.

Second, I feed in changes in the stock of capital equipment (K_t) from the data, while holding all other variables constant. Capital equipment accumulation acts as the primary driver of skill-biased technical change and generates changes in factor shares over time. Cheaper capital equipment induces firms to substitute low-skill workers with equipment. Meanwhile, firms increase the demand for high-skill labor, which complements capital equipment.

My calibrated model shows that changes in K_t are the dominant factor behind the rise in the skill premium in both models. In the homothetic model, if equipment accumulation were the only factor driving the relative demand for skilled labor, the skill premium would increase by 35.0%, accounting for 87.0% of the total predicted increase. In the nonhomothetic model, equipment accumulation leads to an even larger increase in the skill premium due to the added income effect. In this case, the skill premium increases by 35.5%, although the contribution of equipment falls to 81.8%, as aggregate TFP growth also plays a role in the rising wage inequality in the nonhomothetic model.

Finally, I isolate the impact of relative TFP growth, holding all other factors constant. Differences in TFP growth and factor intensities influence the skill premium through a price substitution effect. Consumption shifts toward industries with higher TFP growth and greater exposure to declines in the cost of capital equipment, while moving away from industries more exposed to rising skilled labor costs. This shift in demand operates even without nonhomothetic preferences. In the homothetic model, relative TFP growth leads to a 3.9% increase in the relative wage, accounting for 9.7% of the total rise in the skill premium. When nonhomothetic preferences are introduced, the rise is further amplified through an income effect, resulting in a 4.2% increase in the relative wage,

[22] There is a slight negative effect on relative wages in the homothetic model due to changes in A_t and S_t because consumption shifts towards goods that are more capital structure-intensive, which tend to be marginally less skill-intensive.

contributing to 9.6% of the overall increase.

When the factors mentioned above are independent, the sum of the increases from each channel should equal 100%. In the homothetic model, the additive sum is 96.0%, and in the nonhomothetic model, it is 96.4%, suggesting a small reinforcement effect between these forces. This interaction arises from the positive correlation between industry-level technology growth and capital equipment intensity, as shown earlier in Figure 4b. Consumption shifts toward faster-growing industries, which tend to be more equipment-intensive, thus amplifying the effect of capital-skill complementarity driven by the increase in the stock of capital equipment.

For robustness checks, I redo the quantitative exercises using the capital-skill complementarity elasticities from Krusell et al. (2000) and using the TFP series from BLS. My results, shown in table 8 and 9, largely remain consistent with the baseline model.

Table 6: Decomposition

	Homothetic ($\gamma_{it} = 1$, A_{it}^{GDP})		Nonhomothetic(A_{it}^{GDP})	
	ΔW_t^H	Decomposition	ΔW_t^H	Decomposition
Total	40.2%	100%	43.5%	100%
$\Delta A_t + \Delta S_t$	-0.3%	-0.7%	2.2%	5.0%
ΔK_t	35.0%	87.0%	35.5%	81.8%
ΔA_{it}	3.9%	9.7%	4.2%	9.6%

5.2 Comparison with the literature

Buera et al. (2022) and Comin et al. (2022) mentions a similar mechanism to mine in their paper. They both argue that changes in demand composition, driven by skill-neutral technology advancements, have significantly influenced the increase in skill demand. Calibrated to the World KLEMS data, Buera et al. (2022) predicts a 41.4% overall increase in the skill premium, while Comin et al. (2022), utilizing the CPS, forecasts a 26.6% rise. Buera et al. (2022) use a two-sector model with two skill levels and find that the sector-specific skill-neutral component of technical change (which is equivalent to the combined contribution of A_{it}, A_t and S_t in my model), contributes to 18-24% of the total increase in the skill premium. Meanwhile, Comin et al. (2022), using a three-skill, eight-sector model, identify a 29% increase in wages between high- and middle-skill workers due to the income-driven channel, which includes aggregate productivity growth and labor productivity growth common to all workers.

There are many differences in methodology between their studies and mine. First, my model significantly differs regarding the treatment of capital. Buera et al. (2022) lack capital and assume all skill-biased technical advancements affect the skill premium through changes in factor shares, which is a combination of many other factors that affects the skill premium. Comin et al. (2022) introduces capital into the system, primarily focusing on a Cobb-Douglas production function with an assumed elasticity of substitution across all factors to be one. In their extension model, they consider a CES production function with an elasticity of substitution across occupations of 1.42, yet capital-skill complementarity is still unaddressed. Incorporating capital-skill complementarity gives a larger role for the increase in the stock of capital equipment in my model.

Then, on the empirical side, while both Buera et al. (2022) and Comin et al. (2022) classify skilled workers as those holding a college degree, I adopt the O*NET *Job Zone* classification system for defining skill levels. The skilled workers in my classification have higher average wage compared to theirs, thus experienced a larger growth in skill premium.

In addition, we differ in the how we account for the input-output structure. In my paper, I use the *final expenditure approach* according to Herrendorf et al. (2013) and collapsed the economy on the production side. Thus, my measurement of skill intensities for the final-demand industries takes into account the entire value-chain, and my demand elasticities from Hubmer (2023) is estimated based on the final demand. In both Buera and Kaboski (2012) and Comin et al. (2022), they use the *value-added approach* and collapsed the economy on the demand side. More specifically, they use the factor intensities from final-good industries, while the final demand takes into account the consumption throughout the value chain. As a result, in comparison to their industry-level skill intensities, the distribution of skill intensities across industries in my calibration has a smaller variance, while the final demand consumption across industries are more dispersed. Thus, reallocation in consumption across industries generating from skill-neutral productivity growth (A_t, S_t) have smaller effects on the increase in skill premium in my model. Therefore, I interpret my decomposition for the income-driven consumption channel as the lower-bound.

To assess the importance of this calibration of industry-level skill intensity, I increase the variance of the parameter governing skill intensity (α_i) by scaling the demeaned values by 1.5 and imposing a lower bound of 0.01 for α. This raises the variance of α from 0.076 to 0.113. The resulting decomposition is reported in Table 7.

With these adjusted α_i values, wage growth attributable to skill-neutral technology growth (A_t, S_t, A_{it}) rises, since shifts in consumption across industries now have a larger effect on wages. Specifically, the contribution of aggregate TFP growth increases from 5.0% to 8.0%, the contribution of capital equipment accumulation falls from 81.8% to 73.5%, and the contribution of industry-level productivity growth rises from 9.6% to 16.3%.

Notably, the quantitative analysis is less sensitive to changes in expenditure elasticities. To test this, I also examined the effect of assuming a greater dispersion in expenditure elasticities compared to the baseline model, while keeping skill intensities consistent with the baseline estimates. The results, shown in Appendix B.4, are very similar to the baseline findings, suggesting that variations in expenditure elasticities have a minor effect as long as the positive relationship between expenditure elasticities and skill intensities is preserved.

Table 7: This table presents the baseline counterfactual results when the variance of skill intensity, denoted by α_i in the model, is doubled.

	Nonhomothetic(A_{it}^{GDP})	
	ΔW_t^H	Decomposition
Total	41.5%	100%
$\Delta A_t + \Delta S_t$	3.3%	8.0%
ΔK_t	30.5%	73.5%
ΔA_{it}	6.7%	16.3%

6 Conclusion

Utilizing detailed household consumption data alongside a novel employment dataset, I observe that households with higher incomes allocate a larger proportion of their expenditure towards skill-intensive goods and services. Moreover, I find that over time, all households have increased their consumption share of such goods and services. These findings suggest that economic growth generates higher demand for skilled workers in the labor market, constituting an additional driver of the rising skill premium beyond the extensively discussed skill-biased technical change channel.

To better understand this phenomenon, I develop a multi-industry model of structural transformation featuring two levels of worker skill. In this model, skill-neutral technology growth drives income growth, consequently affecting the skill premium through changes in consumption patterns. On the other hand, capital accumulation serves as the source of SBTC and production-side structural change, influencing the skill premium through capital-skill complementarity and variations across industries in factor intensities. By calibrating the model to match US data from 1982 to 2019, I quantify the significance of this mechanism in the substantial rise in the skill premium.

My quantitative model generates a 43.5% increase in the relative wage of skilled workers. Among this increase, skill-neutral technical change accounts for 14.6% of the total increase, while the bulk is attributed to capital accumulation. I further separate the price substitution effect and the income effect, both of which mainly arise from an industry-level skill-neutral technology growth. Considering a disaggregated economy and accounting for capital-skill complementarity are important for quantifying the contribution of each channel.

For future papers, it would be interesting to expand the model with endogenized labor supply in order to study the welfare implications of different tax policies aimed at mitigating the rise in wage inequality. Consumption upgrading may have important implications for identifying the most effective tax policies to achieve higher equity while maximizing efficiency.

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7 Appendix A: Additional tables and figures

7.1 Main results using BLS TFP series

I redo the quantitative exercises using A_{it}^{BLS}. The results, displayed in Table 8, are similar to those from my baseline analysis. Because my calibrated aggregate TFP growth is slightly higher than the BLS estimates, the impact on the relative wage increase from $A_t + S_t$ is marginally larger in my baseline model.

Table 8: Decomposition using BLS TFP

	Homothetic (γ_{it} = 1, A_{it}^{BLS})		Nonhomothetic(A_{it}^{BLS})	
	ΔW_t^H	Decomposition	ΔW_t^H	Decomposition
Total Increase	40.2%	100%	43.2%	100%
$\Delta A_t + \Delta S_t$	-0.3%	-0.7%	1.9%	4.3%
ΔK_t	35.0%	87.0%	35.5%	82.4%
ΔA_{it}	3.7%	9.1%	3.8%	8.7%

7.2 Main results under capital-skill complementarity elasticities from Krusell et al. (2000)

I redo the quantitative exercises using the capital-skill complementarity elasticities from Krusell et al. (2000). The results, shown in Table 9, are largely consistent with the baseline model. Their estimation of the elasticity of substitution between capital equipment and two types of workers are both larger compared with my estimates of 1.26 and 0.45. In my model, higher complementarity with capital equipment for skilled labor generates larger growth in the skill premium with the same exogenous change in stock of capital, because there is a higher degree of complementarity between equipments and both types of workers. When using their estimation of 1.67 for ρ and 0.67 for η, my model with non-homothetic preferences predicts a 31.5% increase in the relative wage of skilled workers. My estimation also implies slightly smaller degree of capital-skill complementarity ($\rho - \eta$). As a result, accumulation of capital equipment contributes slightly less to the overall increase in skill premium. Using their estimates, the increase in capital equipment K_t contributes to 86.1% of the overall increase in skill premium, while skill-neutral component contributes to 10.7% of the increase.

Table 9: Decomposition using capital-skill complementarity elasticities from Krusell et al. (2000)

	Homothetic (γ_{it} = 1)		Nonhomothetic	
	ΔW_t^H	Decomposition	ΔW_t^H	Decomposition
Total Increase	29.0%	100%	31.5%	100%
$\Delta A_t + \Delta S_t$	-0.2%	-0.8%	1.6%	5.1%
ΔK_t	26.5%	91.4%	27.2%	86.1%
ΔA_{it}	1.9%	6.6%	2.0%	6.4%

7.3 Main results using Stone-Geary utility function

In Figure 10, I present the results of the quantitative analysis based on the Stone-Geary utility function described in Appendix A.4. The overall increase in the skill premium, as well as the contribution of each factor, closely aligns with the predictions from the baseline model. As highlighted in the main text, consumption upgrading has both an amplifying effect and a decomposition effect on wage inequality.

Table 10: Decomposition using Stone-Geary utility function with fixed parameters

	Homothetic ($z = 1$)		Nonhomothetic	
	ΔW_t^H	Decomposition	ΔW_t^H	Decomposition
Total Increase	37.9%	100%	43.0	100%
$\Delta A_t + \Delta S_t$	-3.2%	-8.5%	1.8%	4.2%
ΔK_t	29.7%	78.3%	41.4%	96.2%
ΔA_{it}	2.6%	6.9%	3.0%	7.0%

7.4 Main results using alternative expenditure elasticities

To understand the sensitivity of results to the expenditure elasticities, I double the variance of the expenditure elasticities and redo the main analysis. The results are shown in Table 11. Both the level and the contribution of each channel are very close to the main results, suggesting that changes in the dispersion of expenditure elasticities do not affect my results much, as long as the positive relationship between expenditure elasticities and skill intensities are preserved.

Table 11: Decomposition using Stone-Geary utility function with fixed parameters

	Nonhomothetic(A_{it}^{GDP})	
	ΔW_t^H	Decomposition
Total Increase	27.0%	100%
$\Delta A_t + \Delta S_t$	1.6%	5.9%
ΔK_t	23.4%	86.5%
ΔA_{it}	1.6%	5.9%

8 Appendix B: Model Derivation

8.1 Derivation of price index

In this section, I derive equations 6, 7 and **??**. For calculation simplicity, I break down the derivation into two parts.

Cobb-Douglass price aggregator P_{it}. First, I derive the price of the final good, taking the input prices P^X_{it} and R^S_t as given:

$$\underset{k^S_{it}, X_{it}}{Max}\, P_{it} A_{it} \left(A^S_{it} k^S_{it} \right)^{\beta_i} (X_{it})^{1-\beta_i} - R^S_t k^S_{it} - P^X_{it} X_{it} \tag{21}$$

The first order conditions give

$$k^S_{it} = \frac{\beta_i P_{it} Y_{it}}{R^S_t} \tag{22}$$

$$X_{it} = \frac{(1-\beta_i) P_{it} Y_{it}}{P^X_{it}} \tag{23}$$

Combining the FOCs and the production function $Y_{it} = A_{it}(K^S_{it})^{\beta_{it}}(X_{it})^{1-\beta_{it}}$, I get the final good price in equation 6.

CES price aggregator. Then I solve for the price for Y^X_{it}. Taking the input prices W^H_t and P^M_{it} as given, the firm's problem is equivalent to solving the following profit maximization problem:

$$\underset{h_{it}, M_{it}}{Max}\, P^X_{it} \left[\alpha_i^{\frac{1}{\eta}} H_{it}^{\frac{\eta-1}{\eta}} + (1-\alpha_i)^{\frac{1}{\eta}} M_{it}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} - W^H_t h_{it} - P^M_{it} M_{it} \tag{24}$$

The first order conditions give

$$H_{it} = \left(\frac{P^X_{it}}{W^H_t / A^H_{it}} \right)^{\eta} X_{it} \alpha_i \tag{25}$$

$$M_{it} = \left(\frac{P^X_{it}}{P^M_{it}} \right)^{\eta} X_{it} (1-\alpha_i) \tag{26}$$

Combining the first order conditions with aggregator $X_{it} = \left[\alpha_i^{\frac{1}{\eta}} H_{it}^{\frac{\eta-1}{\eta}} + (1-\alpha_i)^{\frac{1}{\eta}} M_{it}^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$, I get equation 7. Similarly, I can write the input price of M_{it} as equation **??**.

8.2 Calibration of production parameters

Plug in P_{it}^{M} from equation **??** into the relative factor share of low-skill workers θ_{it}^{L}, I can rewrite 13 as

$$\frac{\theta_{it}^{L}}{\theta_{it}^{M}} = \frac{\delta_i}{\delta_i + (1-\delta_i)\left(\frac{R_t^E / A_{it}^E}{W_t^L / A_{it}^L}\right)^{1-\rho}} \tag{27}$$

The difficulty here is that $\frac{R_t^E / A_{it}^E}{W_t^L / A_{it}^L}$ is unobserved in the data. However, within reasonable parameter value of ρ and the range of model-predicted $\frac{R_t^E / A_{it}^E}{W_t^L / A_{it}^L}$, $\delta_i + (1-\delta_i)\left(\frac{R_t^E / A_{it}^E}{W_t^L / A_{it}^L}\right)^{1-\rho}$ is approximately 1. Thus, I set

$$\delta_i = \frac{\theta_{i,2003}^{L}}{\theta_{i,2003}^{M}} = \frac{\theta_{i,2003}^{L}}{\theta_{i,2003}^{L} + \theta_{i,2003}^{E}} \tag{28}$$

Similarly, I can plug in equation 7 into θ_{it}^{H} and rewrite equation 12 as

$$\frac{\theta_{it}^{H}}{1-\beta_i} = \frac{\alpha_i}{\alpha_i + (1-\alpha_i)\left(\frac{p_{it}^M}{W_t^H / A_{it}^H}\right)^{1-\eta}} \tag{29}$$

It follows from equation 28 that p_{it}^{M} is 1. Then, within reasonable estimate of η, $\left(\frac{p_{it}^M}{W_t^H / A_{it}^H}\right)^{1-\eta}$ approximates 1. Thus, I set

$$\alpha_i = \frac{\theta_{i,2003}^{H}}{1-\theta_{i,2003}^{S}} \tag{30}$$

I have also tried different values for $\left(\frac{R_t^E / A_{it}^E}{W_t^L / A_{it}^L}\right)^{1-\rho}$ and $\left(\frac{p_{it}^M}{W_t^H / A_{it}^H}\right)^{1-\eta}$ to calibrate δ_i and α_i, my baseline model prediction is largely the same.

8.3 Derivation of demand function for Stone-Geary preferences

For writing simplicity, I ignore the household type superscript h. Let $\tilde{I}_t$ denote the non-wage incomes. Given prices and wages, the household choose consumption to maximize the utility:

$$\underset{\{C_{it}\}_{i\in I},N_t}{Max} \left(\sum_i a_i(C_{it}-\bar{z}_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} - \chi\frac{N_t^{1-\psi}}{1-\psi} + \lambda\left(W_tN_t + \tilde{I}_t - \sum_i P_{it}C_{it}\right) \tag{31}$$

Rewrite $X_{it} = C_{it} - \bar{z}_i$. For writing simplicity, let $\tilde{I}_t = R_t^S K_t^S + R_t^E K_t^E$. The consumer maximization problem becomes

$$\underset{\{X_{it}\}_{i\in I}}{Max} \left(\sum_i a_i(X_{it})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} - \chi\frac{N_t^{1-\psi}}{1-\psi} + \lambda\left(W_tN_t + \tilde{I}_t - \sum_i P_{it}(X_{it}+\bar{z}_i)\right) \tag{32}$$

The first order condition gives:

$$\left(\sum a_i(X_{it})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} a_i(X_{it})^{-\frac{1}{\sigma}} = \lambda P_{it} \tag{33}$$

$$\chi N_t^{-\psi} = \lambda W_t \tag{34}$$

Taking the ratio of the two equations, I can write the supply of labor as:

$$N_t^{\psi} = \frac{\chi P_{it}}{a_i W_t} X_{it}^{\frac{1}{\sigma}} \left[\sum a_i^{\sigma} X_{it}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{1-\sigma}} \tag{35}$$

Taking the ratio of the first order condition for good i and some base good 0, I can write the demand for good X_{it} as a function of some base good X_{0t}:

$$X_{it} = X_{0t}\left(\frac{P_{0t}a_i}{a_0 P_{it}}\right)^{\sigma} \tag{36}$$

It follows that,

$$\left(\sum a_i^{\sigma} X_{it}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{1-\sigma}} = X_{0t}^{-\frac{1}{\sigma}}\frac{a_0}{P_{0t}}\left(\sum a_i^{\sigma} P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{37}$$

Plugging equation 36 and 37 into equation 35 gives

$$N_t^{\psi} = \frac{\chi}{W_t}\left(\sum a_i^{\sigma} P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{38}$$

Then, from the budget constraint, I get

$$W_t^{\frac{\psi-1}{\psi}}\left[\chi\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}\right]^{\frac{1}{\psi}}+\tilde{I}_t=X_{0t}\left(\frac{P_{0t}}{a_0}\right)^\sigma\sum a_i^\sigma P_{it}^{1-\sigma}+\sum P_{it}\bar{z}_i \tag{39}$$

Thus,

$$N_t^\psi=\frac{\chi}{W_t}\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{40}$$

Then, I can get equation **??**.

$$X_{0t}=\left(\frac{a_0}{P_{0t}}\right)^\sigma\left[\frac{W_t^{\frac{\psi-1}{\psi}}\left[\chi\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}\right]^{\frac{1}{\psi}}}{\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)}+\frac{\tilde{I}_t-\sum P_{it}\bar{z}_i}{\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)}\right] \tag{41}$$

Plugging X_{0t} into equation 36 gives

$$X_{it}=\left(\frac{a_i}{P_{it}}\right)^\sigma\left[\frac{W_t^{\frac{\psi-1}{\psi}}\left[\chi\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}\right]^{\frac{1}{\psi}}}{\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)}+\frac{\tilde{I}_t-\sum P_{it}\bar{z}_i}{\left(\sum a_i^\sigma P_{it}^{1-\sigma}\right)}\right] \tag{42}$$

Thus, I get equation **??**.

8.4 Calibration of the Stone-Geary utility function

In this section, I explain the calibration process for the Stone-Geary utility function used in the welfare analysis. Following Sancho Pifarré (2023), I calibrate the utility function as described earlier. All households are assumed to have identical preferences, which implies uniform expenditure elasticities and preference parameters across households. While the elasticity of substitution σ is taken from Hubmer (2023), I still need to calibrate the preference weight a_i and subsistence consumption levels $\bar{z}_i$ for each good i.

Denote the vector of prices as $P=\{P_i\}_{i\in I}$ and let $s_i(P)=\frac{a_i^\sigma P_{it}^{-\sigma}}{\sum a_i^\sigma P_{it}^{1-\sigma}}$. In the initial year, all prices are normalized to be 1, thus we can rewrite $s_i(1)$ as

$$s_i(1) = \frac{a_i^\sigma}{\sum_i a_i^\sigma} \tag{43}$$

Next, I derive the expenditure elasiticities from equation **??** and express it as a function of the consumption share ω_{it} and $s_i(P)$:

$$\begin{aligned}
\gamma_i &= \frac{\partial C_i}{\partial E}\frac{E}{C_i} = \frac{a_i^\sigma P_i^{-\sigma}}{\sum a_i^\sigma P_i^{1-\sigma}}\frac{E}{C_i} \\
&= \frac{a_i^\sigma P^{1-\sigma}}{\sum a_i^\sigma P_i^{1-\sigma}}\frac{E}{P_i C_{it}} \\
&= \frac{s_i(P)}{\omega_{it}(P)}
\end{aligned} \tag{44}$$

Given the substitution elasticity σ and the expenditure elasticities γ_i estimated by Hubmer (2023), as well as the consumption share from the data, I can determine $s_i(1)$ and thus solve for a_i using equation 43.

$$\frac{a_i^\sigma}{\sum_i a_i^\sigma} = \gamma_{it}\omega_{it} \tag{45}$$

The system, however, only identifies the relative coefficient of a_i. Therefore, I impose restrictions $\sum_i a_i = 1$ to uniquely determine all values of a_i. Note that a_i is positively correlated with the expenditure elasticities and consumption shares. Thus, an inferior good with low consumption share would be assigned a low weight in the utility function.

The next step is to calculate the subsistence parameter z_i. I utilize the money elasticity $\phi = -2$ from Frisch (1959), which measures the flexibility in the distribution of income between the fixed and the variable parts of consumption. At the initial period with normalized prices, the money elasticity depends on total income E_t and minimum level of consumption z_i:

$$-\phi = \frac{E_t}{E_t - \sum_i z_i} \tag{46}$$

Substituting it into the demand function **??** gives

$$z_i = C_{it} - s_i(1)\frac{E_t}{-\phi} \tag{47}$$

To calibrate the parameters, I use consumption shares and expenditure elasticities from the data in the initial period, along with model-generated prices, outputs, and aggregate income corresponding to the equilibrium solution in the baseline model's initial period.

9 Appendix C: Industry-specific TFP growth

9.1 Comparison to BLS TFP for selected industries

The BLS provides total factor productivity (TFP) estimates for several major industries, primarily within the manufacturing sector, starting from 1987.[23] Figure 5 compares my calibrated industry-level TFP growth with BLS-estimated TFP for 20 industries at the 3-digit NAICS level. To compute TFP growth at the 3-digit level, I take the unweighted average of all industries within each group. Overall, my calibrated TFP shows trends that closely align with BLS estimates for most industries.

9.2 List of all industries

Table 12 and 13 show the average annual growth rate of for 133 final-goods industries from 1982 to 2019. Annual growth rate is calculated as the percentage change in TFP from a year ago. To calibrate the industry-level TFP growth, I match the per capital GDP growth and the change in relative prices over the sample period. The detailed calibration process is described in the main text.

[23]Source: U.S. Bureau of Labor Statistics. `https://www.bls.gov/productivity/tables/`

Figure 5: Model calibrated TFP growth rate vs. BLS estimated TFP growth rate

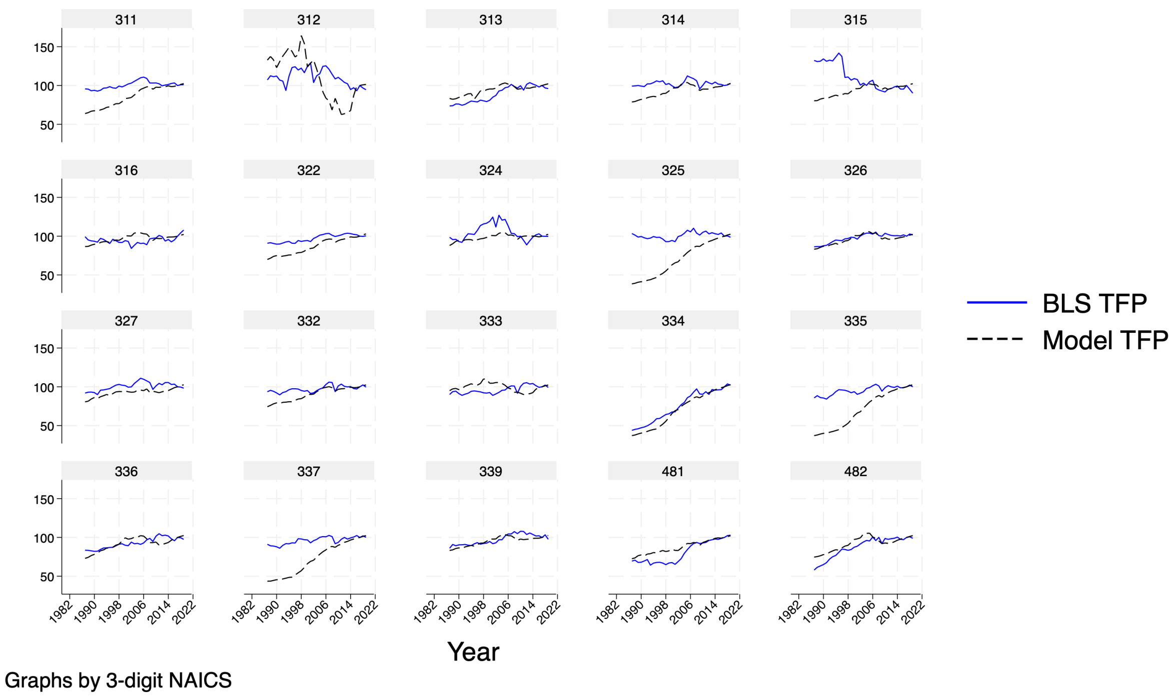

Table 12: Calibrated TFP growth

NAICS code	Industry Title	ΔA_{it}
oohre	OOH + Real Estate	-0.0134
541100	Legal services	-0.0090
52A000	Monetary authorities and depository credit intermediation	-0.0034
623000	Nursing and residential care facilities	-0.0033
512100	Motion picture and video industries	-0.0024
522A00	Nondepository credit intermediation and related activities	-0.0024
712000	Museums, historical sites, zoos, and parks	-0.0021
622000	Hospitals	-0.0021
611B00	Other educational services	-0.0011
812900	Other personal services	-0.0004
711200	Spectator sports	-0.0002
3122A0	Tobacco product manufacturing	0.0004
621B00	Medical and diagnostic labs and outpatient and other ambulatory care services	0.0005
624400	Child day care services	0.0006
621A00	Offices of physicians, dentists, and other health practitioners	0.0010
7211A0	Hotels and motels, including casino hotels	0.0010
621600	Home health care services	0.0011
23	Construction	0.0011
812100	Personal care services	0.0013
325610	Soap and cleaning compound manufacturing	0.0014
812300	Dry-cleaning and laundry services	0.0015
811400	Personal and household goods repair and maintenance	0.0016
524100	Insurance carriers	0.0018
325620	Toilet preparation manufacturing	0.0019
611A00	Junior colleges, colleges, universities, and professional schools	0.0019
722000	Food services and drinking places	0.0022
325320	Pesticide and other agricultural chemical manufacturing	0.0023
325412	Pharmaceutical preparation manufacturing	0.0024
611100	Elementary and secondary schools	0.0027
221200	Natural gas distribution	0.0033
713A00	Amusement parks, arcades, and gambling industries	0.0034
48A000	Scenic and sightseeing transportation and support activities for transportation	0.0037
221100	Electric power generation, transmission, and distribution	0.0039
325510	Paint and coating manufacturing	0.0041
8111A0	Automotive repair and maintenance, except car washes	0.0041
492000	Couriers and messengers	0.0041
812200	Death care services	0.0043
532100	Automotive equipment rental and leasing	0.0045
532230	Video tape and disc rental	0.0049
3259A0	All other chemical product and preparation manufacturing	0.0051
561700	Services to buildings and dwellings	0.0053
813B00	Civic, social, professional, and similar organizations	0.0053
811200	Electronic and precision equipment repair and maintenance	0.0054
532400	Commercial and industrial machinery and equipment rental and leasing	0.0055
541940	Veterinary services	0.0055
562000	Waste management and remediation services	0.0056
561900	Other support services	0.0057
322291	Sanitary paper product manufacturing	0.0059
311000	Food at Home	0.0061
312100	Alcohol	0.0062
485000	Transit and ground passenger transportation	0.0063
532A00	General and consumer goods rental except video tapes and discs	0.0067
221300	Water, sewage, and other systems	0.0071
32712A	Brick, tile, and other structural clay product manufacturing	0.0074
561600	Investigation and security services	0.0075
541200	Accounting, tax preparation, bookkeeping, and payroll services	0.0078
337910	Mattress manufacturing	0.0081
322230	Stationery product manufacturing	0.0083
337122	Nonupholstered wood household furniture manufacturing	0.0087
337212	Office furniture and custom architectural woodwork and millwork manufacturing	0.0087
33712A	Metal and other household furniture (except wood) manufacturing	0.0089
327212	Other pressed and blown glass and glassware manufacturing	0.0089

Table 13: Calibrated TFP growth

NAICS code	Industry Title	ΔA_{it}
337121	Upholstered household furniture manufacturing	0.0096
33221A	Cutlery, utensil, pot, and pan manufacturing	0.0097
483000	Water transportation	0.0097
482000	Rail transportation	0.0097
515200	Cable and other subscription programming	0.0097
337920	Blind and shade manufacturing	0.0099
481000	Air transportation	0.0099
32711A	Pottery, ceramics, and plumbing fixture manufacturing	0.0100
332913	Plumbing fixture fitting and trim manufacturing	0.0101
333991	Power-driven handtool manufacturing	0.0105
337110	Wood kitchen cabinet and countertop manufacturing	0.0106
336991	Motorcycle, bicycle, and parts manufacturing	0.0108
491000	Postal service	0.0109
333415	Air conditioning, refrigeration, and warm air heating equipment manufacturing	0.0110
333112	Lawn and garden equipment manufacturing	0.0110
336612	Boat building	0.0112
333315	Photographic and photocopying equipment manufacturing	0.0114
486000	Pipeline transportation	0.0114
33221B	Handtool manufacturing	0.0116
32619A	Other plastics product manufacturing	0.0117
212100	Coal mining	0.0117
333618	Other engine equipment manufacturing	0.0118
511130	Book publishers	0.0121
339930	Doll, toy, and game manufacturing	0.0123
333319	Other commercial and service industry machinery manufacturing	0.0124
335228	Other major household appliance manufacturing	0.0125
339113	Surgical appliance and supplies manufacturing	0.0127
335210	Small electrical appliance manufacturing	0.0127
33331A	Vending, commercial, industrial, and office machinery manufacturing	0.0130
326210	Tire manufacturing	0.0131
339940	Office supplies (except paper) manufacturing	0.0131
335120	Lighting fixture manufacturing	0.0132
335221	Household cooking appliance manufacturing	0.0133
339112	Surgical and medical instrument manufacturing	0.0134
335222	Household refrigerator and home freezer manufacturing	0.0135
339115	Ophthalmic goods manufacturing	0.0136
484000	Truck transportation	0.0136
335224	Household laundry equipment manufacturing	0.0137
33329A	Other industrial machinery manufacturing	0.0138
4A0000	Retail trade	0.0140
339920	Sporting and athletic goods manufacturing	0.0140
511120	Periodical publishers	0.0140
33999A	All other miscellaneous manufacturing	0.0142
339992	Musical instrument manufacturing	0.0143
339910	Jewelry and silverware manufacturing	0.0145
511110	Newspaper publishers	0.0146
314110	Carpet and rug mills	0.0158
314120	Curtain and linen mills	0.0167
315200	Apparel	0.0170
313100	Fiber, yarn, and thread mills	0.0172
316900	Other leather and allied product manufacturing	0.0172
313210	Broadwoven fabric mills	0.0176
336110	Car and Other Vehicles	0.0181
315100	Apparel knitting mills	0.0181
316200	Footwear manufacturing	0.0181
517000	Telecommunications	0.0182
420000	Wholesale trade	0.0182
111400	Greenhouse, nursery, and floriculture production	0.0188
315900	Apparel accessories and other apparel manufacturing	0.0195
336300	Motor vehicle parts manufacturing	0.0197
336214	Travel trailer and camper manufacturing	0.0198
493000	Warehousing and storage	0.0232
324110	Petroleum refineries	0.0254
324191	Petroleum lubricating oil and grease manufacturing	0.0277
211000	Oil and gas extraction	0.0427
334613	Magnetic and optical recording media manufacturing	0.0705
334210	Telephone apparatus manufacturing	0.0720
334300	Audio and video equipment manufacturing	0.0723
334111	Electronic computer manufacturing	0.0725
334290	Other communications equipment manufacturing	0.0743
33451A	Other Measuring and Controlling Device Manufacturing	0.0745