The distributional impact of sectoral technical change

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October 2023

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Abstract

The economic impact of sectoral technical change has long been recognized as an important phenomenon. However, the distributional welfare consequences of these changes are not well understood. To address this gap, we develop an analytical framework that jointly integrates supply-side and demand-side heterogeneity. Without imposing structural restrictions on the consumption and production sides, the framework identifies the key forces—in terms of consumer preferences and sectoral production functions—shaping the welfare effects of sectoral technical changes. We estimate key parameters and quantify the heterogeneous welfare effects of sectoral technical changes, revealing significant variation in their impact. Finally, we show how our general framework can be applied to other exogenous sectoral changes by analyzing the distributional welfare impact of sectoral demand shifters.

1. Introduction

Sectoral technical changes have long been acknowledged as pivotal for economic growth. As vividly described in Harberger's 1998 AEA Presidential Address (Harberger (1998)), growth exhibits characteristics similar to that of "mushrooms" rather than "yeast"; That is, variation in sectoral total factor productivity (TFP) across different industries is substantial.

While the importance of sectoral technical changes is well-established, their distributional welfare consequences are not well understood. This paper aims to bridge this knowledge gap by developing a comprehensive analytical framework that captures the welfare effects of sectoral technical change, focusing on the disparate welfare impact between low-skilled and high-skilled individuals. By analyzing theoretically and quantifying empirically the interplay between consumer preferences and sectoral production functions within a general equilibrium framework, we shed light on the mechanisms through which sectoral changes affect wages, goods prices, and hence, ultimately, welfare outcomes.

Our framework, which does not impose any functional form restrictions on preferences and production, integrates supply-side and demand-side heterogeneity, which, as we show below, is crucial in understanding welfare effects. The framework identifies analytically four key factors influencing the welfare impact of sectoral technical change: income elasticities of consumption goods, consumption substitution patterns, consumption shares of the different goods, and the skill intensity of the sector experiencing technical change relative to the economy. Turning to the empirical estimates, our findings indicate that sectoral technical changes impact high and low-skilled workers' welfare differently, and these differential effects are contingent upon the aforementioned factors.

We begin our analysis in Section 2 where we develop a general multi-sectoral model featuring workers of heterogeneous skills. Workers derive utility from consuming a bundle of goods and can have non-homothetic preferences. On the production side, goods are produced in different sectors which vary in their skill intensity.

Using this framework, in Section 3 we show that the distributional welfare impact of sectoral technical change can be decomposed into two distinct effects. The first effect, which we refer to as the "Engel effect", stems from the fact that with non-homotheticities, consumers of different income levels consume different bundles with different expenditure shares. As a result, price changes stemming from sectoral technical changes, benefit deferentially agents with different income. This effect is in the spirit of the inflation inequality literature (for a survey see, e.g., Jaravel (2021*a*)).

The Skill Premium effect, our second effect, arises because sectoral technical change shifts demand for goods. As sectors vary in skill intensity, this demand shift alters relative wages, i.e. the skill premium. To understand the Skill Premium effect, in our theoretical analysis in Section 3 we solve analytically for the equilibrium elasticity of the skill premium with respect to a sectoral technical change. Our analytical analysis shows that income elasticities of consumption goods, the patterns of consumption substitution in the economy, and the relative skill intensity of the sector experiencing technical change are the key determinants of the skill premium effect.

Importantly, our framework also allows us to directly calculate the differential welfare effect using model primitives (price and income elasticities, expenditure shares, and high- and low-skilled labor shares). We rely on this in taking the model to the data in Section 4. As discussed above, our framework allows to do so without imposing structural restrictions on the consumption and production sides. This is important given that the analytical results highlight the importance of allowing for flexibility in key model primitives, and especially substitution patterns in the demand system.

Relying on the analytical results, we use data from the Consumer Expenditure Survey (CEX) to estimate an Almost Ideal Demand System (AIDS) from which we recover the key price and income elasticities. We use the Current Population Survey (CPS) to recover labor shares by skill level, and KLEMS data for sectoral productivity dynamics. Finally, we use an input-output matrix to map the measures obtained from the CPS and KLEMS to consumption categories.

Armed with these data, we conduct two empirical exercises using two different granulation of consumption categories. The first examines the welfare consequences of sectoral technical changes using the consumption categorization common in the structural transformation literature (see, e.g., Buera and Kaboski (2012), Herrendorf, Rogerson and Valentinyi (2014), and Comin, Lashkari and Mestieri (2021)) – Agriculture, Manufacturing, and Services. Then, given our interest in sectoral technical change and our analytic results emphasizing the importance of substitution patterns, in our second empirical exercise we use a finer goods categorization to capture more nuanced substitution patterns.

We discuss our five main quantitative findings in Section 5. First, sectoral technical change affects welfare of high and low-skilled workers differently. Second, this differential effect varies across sectors in both magnitude and sign: using the finer goods categorization, the differential welfare effect between high and low skilled workers ranges between a negative 20% and a positive 70%.

Third, while both the Skill Premium effect and the Engel effect are quantitatively important in determining the overall distributional impact of technical change, it is the former that plays a more important role.

Fourth, our estimates show that gross complementarities are prominent in the substitution matrix. Consistent with our theoretical analysis regarding the role of complementarities, we find a general pattern by which, in response to a positive productivity change, low-skill intensive sectors exhibit a positive Skill Premium effect while high-skill intensive sectors exhibit a negative Skill Premium effect.

In our final quantitative analysis, we calculate the overall differential welfare impact of sectoral technical change on high versus low workers given the empirical changes in sectoral TFP over 1987 to 2019. We find that high-skilled workers enjoyed an overall 8.35% greater welfare increase compared to low-skilled workers.

Our analytical framework is general enough to be applicable to a broad range of scenarios. To illustrate this, we examine in Section 6 the distributional welfare impact of sectoral demand shifts, which result from exogenous changes in sectoral preferences. We analytically derive the primitives that determine the distributional consequences of such demand changes, and guided by this analysis, we estimate their distributional welfare consequences.

Related Literature Our work is linked to three main strands of literature. First, our work relates to the structural change literature, which analyzes how technical change at the aggregate level causes sectoral reallocation of economic activity between manufacturing, services, and agriculture (for recent contributions, see, e.g., Kongsamut, Rebelo and Xie (2001), Buera and Kaboski (2012), Herrendorf, Rogerson and Valentinyi (2013), Matsuyama (2019), Baqaee and Burstein (2021), Comin, Lashkari and Mestieri (2021), Alder, Boppart and Muller (2022) as well as the review in Herrendorf, Rogerson and Valentinyi (2014)). In contrast to this literature, which focuses on the determinants of structural change, we provide a general framework that uncovers the general equilibrium mechanisms governing the differential welfare impact of sectoral technical changes. Clearly, our framework also enables an analysis of the distributional welfare impact of aggregate technical change – by considering the scenario where all sectoral technical changes are equal. Within the structural change literature, closest to our paper is Buera et al. (2022), which explores the implications of structural change to the skill-premium. In addition to the focus on a different motivating question, the Buera et al. (2022) paper and our paper take a very different modelling approach. While they employ specific functional forms – both on the preferences and on the production side – our analytical framework is functional-form free. This allows us to derive analytical results that clarify the forces driving changes to the skill-premium in terms of model primitives; among others these include the crucial role of flexible complementarity and substitutability patterns in demand across goods and their interaction with heterogeneity in skill-intensity across sectors.

Second, our analysis of sectoral technical change is naturally related to the "Baumol cost disease" literature as first discussed by Baumol and Bowen (1965). Using industry level data, Nordhaus (2008) verifies a key prediction of the Baumol effect, whereby technologically stagnant sectors exhibit rising relative prices and declining relative real outputs.[1] These papers focus on a reduced form empirical analysis of the Baumol effect. In contrast, we analytically analyze and empirically estimate the heterogeneous welfare implications of technical change.

Finally, our research is also related to studies that examine the impact of differential price changes on the welfare distribution in contexts where non-homothetic preferences lead consumers with different income levels to have differential consumption baskets. The inflation inequality literature, for instance, delves into how distinct inflation rates across goods, combined with diverse consumption baskets among households, shape welfare outcomes (refer to Jaravel (2021*a*) for a comprehensive survey). Similarly, the international trade literature examines the influence of trade on the relative prices of exported and imported goods and its implications on welfare when accounting for heterogeneous consumption baskets among households (for such a mechanism see Fajgelbaum and Khandelwal (2016)). Our analysis shows that sectoral technical change also impacts the welfare distribution through such a price mechanism: Sectoral technical change affects the relative prices of goods which, given differential consumption shares, will affect the welfare distribution. As explained above, our decomposition result also exhibits an important second mechanism through which sectoral technical change affects the welfare distribution – namely through its impact on relative income levels. As such, our findings emphasize that understanding

[1] Hartwig (2011) shows similar results for Europe.

the overall consequences of sectoral changes on the welfare distribution mandates a model that integrates both supply-side and demand-side heterogeneity.

2. Model

We utilize a static multi-sector model, which enables us to emphasize the fundamental economic mechanisms that shape the distributional welfare impacts of sectoral technical change. We impose minimal constraints on preferences and production, enabling us to identify the essential forces at play without confining ourselves the analysis to restrictive parametric forms. This approach allows us not only to demonstrate the underlying factors driving the distributional welfare impact of sectoral technical change, but also clearly pinpoints the elements that need to be estimated.

2.1. Setup

The general structure of the model is as follows. Workers derive utility from the consumption of a bundle of N different goods. The production of each of the different N goods is performed by perfectly competitive firms that use two inputs – high- and low-skilled labor – and maximize profits. Finally, we assume that workers can move freely across sectors. Consequently, there are only two wages in the economy, one for each skill level. In what follows we formally present the model.

2.1.1. Production

The model is comprised of N sectors, each producing a different good. Sector i produces Y_i goods using the following constant returns to scale production function:

$$Y_i = A_i F^i(L_i, H_i), \forall i \in N,$$

where L_i and H_i are low- and high-skilled labor inputs respectively, and A_i is Hicks neutral productivity parameter. The representative firm in sector i solves:

$$\max_{L_i, H_i} P_i Y_i - W_L L_i - W_H H_i.$$

Crucially, the production function F is indexed by i as well, allowing for differential production elasticities of the two inputs across sectors.

2.1.2. Workers

There are two types of workers, l and h. Types are fixed (a worker cannot switch type), with a mass of L and H in the economy of l and h type workers respectively. We normalize the population so that $L+H=1$.

Workers derive utility from the bundle of goods and supply work inelastically. The maximization problem for an individual of type $j \in \{l,h\}$ is thus:

$$\max_{C_{j1},\ldots,C_{jN}} U\left(C_{j1},\ldots,C_{jN}\right)$$
$$\text{s.t. } \sum_{i=1}^{N} P_i C_{ji} = W_j,$$

where P_i is the price of good produced by sector i, and C_{ji} is the consumption of good i by a worker of type j. Throughout, we normalize the price of the sector experiencing the technical change to 1. Importantly, we do not restrict the utility function to be homothetic. Thus, expenditure shares of each type $j \in \{l,h\}$ worker for good i are denoted by $s_i^j \equiv s_i(W_j,\mathbf{P})$, and depend on the worker's wage, W_j, and the price vector $\mathbf{P}$.

2.1.3. Equilibrium

In equilibrium both firms and workers behave optimally and all markets clear. Given the lack of frictions, wages are equated across all markets, and hence workers are indifferent over which market to work in.

Formally, the market for low-skilled labor, denoted as L, is in equilibrium when the total supply of low-skilled labor input matches its demand across the N sectors, i.e.,

$$\sum_{i=1}^{N} L_i = L.$$

Analogously, for the high-skilled labor market H, equilibrium is achieved when

$$\sum_{i=1}^{N} H_i = H.$$

Furthermore, for a low-skilled worker, the budget constraint is satisfied when the expenditure on consumption across all goods equals the wage, i.e.,

$$\sum_{i=1}^{N} P_i C_{l,i} = W_L,$$

where $C_{l,i}$ denotes the consumption of good i by a low-skilled individual. A similar equation holds for a high-skilled individual, where

$$\sum_{i=1}^{N} P_i C_{h,i} = W_H.$$

Lastly, for any sector $i \in N$, the production of its good must be equal to the sum of the demand from both low and high-skilled workers, i.e.,

$$LC_{l,i} + HC_{h,i} = Y_i.$$

Henceforth, we define α_i the equilibrium L labor share of sector i: $\alpha_i = \frac{W_L L_i}{P_i Y_i}$.

2.2. Welfare

Our welfare measure is a variant of the Equivalent Variation measure. Specifically, given any shock that affects equilibrium prices and wages, the welfare change is defined as the incremental income necessary to obtain the post-shock utility at the pre-shock prices and wages. Denoting the expenditure function given prices $\mathbf{p}$ and utility level u to be $e(\mathbf{p}, u)$, then the change in welfare for type j induced by the shock is given by:

$$\widetilde{EV}^j = e(\mathbf{p}_0, u_1^j) - W_0^j,$$

where $\mathbf{p}_0$ are the pre-shock equilibrium prices, u_1^j is the post-shock equilibrium utility for type j, and W_0^j is the pre-shock wage for type j.

Using Roy's identity, a well-known result is that, locally, the welfare change can be decomposed into changes in wages and changes in good prices:

$$\widetilde{EV}^j = dW^j - \Sigma_i C_i(p_0, W_0^j) dp_i.$$

Normalizing the welfare change by the pre-shock wage, and using a circumflex to denote percent deviations from pre-shock levels, we obtain that the percent change in welfare is given by:

$$EV^j := \frac{\widetilde{EV}^j}{W_0^j} = \widehat{W^j} - \Sigma_i s_i(p_0, W_0^j)\widehat{p}_i. \tag{1}$$

Thus, the change in welfare equals the change in the real wage of type j with a type-specific price index, where the weights are given by type-specific consumption shares $s_i(p_0, W_0^j)$.

It follows then from Equation (1), that the difference between types in the welfare change is given by:

$$\Delta EV := EV^H - EV^L = \widehat{\left(\frac{W^H}{W^L}\right)} - \Sigma_i \left(s_i^H(p_0, W_0^H) - s_i^L(p_0, W_0^L)\right)\widehat{p}_i. \tag{2}$$

That is, Equation (2) shows that the change in the welfare distribution over types can be decomposed into a change in the skill premium, $\widehat{\frac{W^H}{W^L}}$, and the difference in the type-specific, share-weighted price changes.

3. Analytical Results

Our key objective is to study the distributional welfare effects of sectoral technical change. In what follows, we consider a Hicks neutral change in productivity to a given sector, $k \in 1...N$, denoted by $\widehat{A}_k$ (while holding all other productivities constant). We employ $\eta_{W^H/W^L,A_k}$ to express the elasticity of the skill premium in relation to the aforesaid change in sectoral productivity. Our analysis begins with the establishment of the following theorem.

Theorem 1. *For a productivity change in any sector k (while holding all other productivities constant), the difference between types in the elasticity of welfare to the productivity change is given by*

$$\Delta\eta_{EV,A_k} := \frac{EV^H}{\widehat{A}_k} - \frac{EV^L}{\widehat{A}_k} = (s_k^H - s_k^L) + \eta_{W^H/W^L,A_k}\left\{1 + \Sigma_i \alpha_i \left(s_i^H - s_i^L\right)\right\}, \tag{3}$$

The proofs for this theorem, as well as all subsequent proofs, can be found in Appendix A.1.

Equation (3) shows that $\Delta\eta_{EV,A_k}$, which measures the distributional welfare impact of the productivity change, can be decomposed into two main objects.

The first object, $s_k^H - s_k^L$, stems from non-homotheticity, reflected in the difference in consumption shares over types. A positive technical change to sector k is directly reflected in a price decline for good k, so that the type that has a larger consumption share of that good will experience a larger welfare gain. In what follows, we refer to this effect as the *Engel effect*.

The second object is comprised of two factors: the elasticity of the equilibrium skill-premium w.r.t. productivity, denoted by $\eta_{W^H/W^L,A_k}$, and an extra term that captures the covariance between the labor share and the difference over types in consumption shares. As we discuss in the Appendix, this covariance term captures the feedback loop between the change in the skill premium and sectoral prices. It is easy to show that the covariance term is positive, and hence the sign of the second term is determined by $\eta_{W^H/W^L,A_k}$.[2] Furthermore, as we discuss below, empirically, the covariance term is very close to 0, implying that the magnitude of the second term is dominated by the skill premium elasticity.

3.1. Signing the Skill-Premium Elasticity

In what follows we analyze the determinants of $\eta_{W^H/W^L,A_k}$. Our motivation stems from the significant role this elasticity plays in dictating the distributional welfare outcomes of sectoral technical change as seen in Equation 3. We begin our analysis with the following lemma.

Lemma 1. *The set of equilibrium conditions of the model, as outlined in Section 2.1.3, can be consolidated into a single market-clearing condition for high-skilled individuals. This condition is solely a function of the exogenous productivities and the skill-premium. Furthermore, this single equation, which we denote as*

$$\mathscr{H}(\mathbf{A}, \frac{W_H}{W_L}) = 0. \tag{4}$$

inherently encompasses all the equilibrium conditions of the other markets. Therefore, it functions as an excess demand equation specifically for the high-skilled labor market.

Equation 4 serves two key purposes. First, it enables us to ascertain what influences the *sign*

[2] To see that the covariance term is positive, note that:

$$1 + \Sigma_i \alpha_i \left(s_i^H - s_i^L\right) = 1 + \Sigma_i \alpha_i s_i^H - \Sigma_i \alpha_i s_i^L \geq 1 + min\{\alpha_i\} - max\{\alpha_i\} > 0,$$

where the last inequality stems from the fact that $\alpha_i \in (0,1)\,\forall i$.

of the skill premium's elasticity with respect to technical change, which we establish in Theorem 2. Second, it helps us understand how this elasticity is determined by the model's primitives – preferences and production functions – which is established in Theorem 3. This last theorem allows for an analytical characterization of the equilibrium based on model primitives and provides guidance regarding the elements we need to estimate.

As a first step, Theorem 2 signs the skill premium elasticity:

Theorem 2. *The sign of the skill premium elasticity w.r.t a technical change in sector k (while holding all other productivities constant) is given by*

$$sign\left(\eta_{W_H/W_L,A_k}\right) = -sign\left\{\frac{d}{dA_k}\left[\sum_{i=1}^{N}\alpha_i\left(S_H s_i^H + S_L s_i^L\right)\right]\right\}, \tag{5}$$

In this equation, $S_H = \frac{W_H H}{(W_H H + W_L L)}$ and $S_L = \frac{W_L L}{(W_H H + W_L L)}$ represent the aggregate expenditure shares of the high-skilled and low-skilled individuals in the economy, respectively. Similarly, s_i^H and s_i^L stand for the consumption share of a sector i as a fraction of the total expenditures for the high-skilled and low-skilled individuals, respectively.

Recall that α_i signifies the labor share of the low-skilled in sector i. Thus, Equation 5 illustrates the importance of whether demand moves either toward or away from the high-skilled sector in influencing the skill-premium. Specifically, when technical change reduces the share weighted α (i.e., when $\sum_{i=1}^{N}\alpha_i\left(S_H s_i^H + S_L s_i^L\right)$ decreases), the economy shifts towards being more high-skill intensive. As might be anticipated, equation (5) indicates that in such a case, the skill-premium increases.

3.2. The Determinants of the Skill Premium Elasticity

The next theorem characterizes the skill premium elasticity–a key determinant of the distributional welfare impact of sectoral technical change–in terms of model primitives. Implicitly differentiating equation (4), and writing the result in terms of an elasticity, we show that:

Theorem 3. *The elasticity of the equilibrium skill-premium w.r.t. a technical change in sector k (while holding all other productivities constant) is given by*

$$\eta_{W^H/W^L,A_k} = -\frac{\eta_{\mathscr{H},A_k}\left(\mathbf{A},\frac{W_H}{W_L}\right)}{\eta_{\mathscr{H},W_H/W_L}\left(\mathbf{A},\frac{W_H}{W_L}\right)} = -\frac{\sum_{i=1}^{N}\alpha_i\left(S_L s_{i,L}\eta_{s_{i,L}P_k} + S_H s_{i,H}\eta_{s_{i,H},P_k}\right)}{G\left(\boldsymbol{\alpha},\boldsymbol{\sigma},S_L,S_H,\mathbf{s}_L,\mathbf{s}_H,\boldsymbol{\eta}^L_{\mathbf{C},\mathbf{P}},\boldsymbol{\eta}^H_{\mathbf{C},\mathbf{P}},\boldsymbol{\eta}^L_{\mathbf{C},\mathbf{W}},\boldsymbol{\eta}^H_{\mathbf{C},\mathbf{W}}\right)}, \tag{6}$$

where $\eta_{\mathscr{H},A_k}$ and $\eta_{\mathscr{H},W_H/W_L}$ denote the partial elasticity of $\mathscr{H}$ w.r.t A_k and W_H/W_L, respectively. $\boldsymbol{\sigma}$ is the vector of elasticity of substitutions of the N production functions. $\eta_{s_{i,L}P_k}$ is the uncompensated elasticity of the consumption share of good i w.r.t P_k for the low skilled. Additionally, $\boldsymbol{\eta}^L_{\mathbf{C},\mathbf{P}}$ denotes the uncompensated price elasticity matrix with element $\{i,j\}$ capturing uncompensated price elasticity of good i to price j. $\boldsymbol{\eta}^L_{\mathbf{C},\mathbf{W}}$ is the vector of Engel elasticities for the L types. $\eta_{s_{i,H}P_k}, \boldsymbol{\eta}^H_{\mathbf{C},\mathbf{P}}$ and $\boldsymbol{\eta}^H_{\mathbf{C},\mathbf{W}}$ are defined analogously for the H types. Finally, G is a real-valued function explicitly defined as:

$$G := S_H \left[\sum_{i=1}^{N} (\alpha_N - \alpha_i) \frac{S_L}{S_H} \Omega_i - \alpha_N + \sum_{i=1}^{N} \left(\alpha_i \frac{W_H H_i}{W_H H} (1 - \sigma_i) \right) \right]$$

with

$$\Omega_i := \left[s_{i,L}(1-\alpha_i) + \begin{pmatrix} . & s_{i,L}\eta^L_{C_i,P_j} & . & s_{i,L}\eta^L_{C_i,W} \end{pmatrix}_{1\times N} * \begin{pmatrix} . \\ \alpha_N - \alpha_j \\ . \\ \alpha_N - 1 \end{pmatrix}_{N\times 1} \right]$$
$$+ \frac{S_H}{S_L} \left[s_{i,H}(1-\alpha_i) + \begin{pmatrix} . & s_{i,H}\eta^H_{C_i,P_j} & . & s_{i,H}\eta^H_{C_i,W} \end{pmatrix}_{1\times N} * \begin{pmatrix} . \\ \alpha_N - \alpha_j \\ . \\ \alpha_N \end{pmatrix}_{N\times 1} \right]$$

In Equation (6) the numerator has the interpretation of the partial equilibrium effect of technical change on excess demand for high-skilled labor while holding constant the skill premium. We discuss below how its sign gets determined in terms of the model's primitives.

The denominator captures the response required in the skill premium in order to maintain excess demand at zero given the change in demand induced by the technical change. In Appendix A.1 we show that if for all sectors i, the elasticity of substitution (σ_i) is greater or equal to 1 (with $\sigma = 1$ being the Cobb-Douglas case), then the denominator is negative. This negative sign is intuitive: when high and low skilled workers are sufficiently substitutable, when the skill premium rises, then the excess demand for high-skilled workers declines.

Returning to the numerator, equation (6) points again to the importance of the share-weighted

α in determining the SP elasticity. However, we note that the weights are defined as functions of preference parameters and specifically, the price elasticities. As such, given a sectoral technical change to a specific sector, the degree to which goods are complements or substitutes dictates the behavior of the share-weighted α. Consider, for example, a decline in the P_k price due to a positive A_k technical change. Aggregate expenditure shares of all goods i, both for the low- and the high-skilled workers will change according to the price elasticity w.r.t. good k. The numerator then captures how these demand shifts are reflected in changes to the share-weighted α.

The results from Theorem 3 allows us to revisit Theorem 2 and establish the condition that determines the sign of the skill-premium elasticity in terms of model primitives. This is summarized in the following lemma:

Lemma 2. *Assume that the denominator in (6) is negative. A sufficient condition for the elasticity of the skill premium $\eta_{W_H/W_L,A_k}$ to be positive is that for each type $T \in \{H,L\}$:*

$$\Sigma_{i=1}^{N}\alpha_i s_i^T \eta_{s_i P_k}^T = s_k^T \alpha_k - s_k^T \Sigma \alpha_i w_i^T > 0, with\ w_i^T = \frac{s_i^T \eta_{c_i P_k}^T}{\Sigma_i s_i^T \eta_{c_i P_k}^T}$$

See proof in Appendix A.1.The lemma results from a decomposition of the numerator in equation (6) into two components. This decomposition stems from the fact that for $i \neq k$, $\eta_{s_i P_k}^T = \eta_{c_i P_k}^T$, while for $i = k$, $\eta_{s_i P_k}^T = 1 + \eta_{c_k P_k}^T$, where the latter stems from the fact that a price change of good k has a direct effect on the expenditure share of good k. The impact on the expenditure share weighted alpha ($s_k^T \alpha_k - s_k^T \Sigma \alpha_i w_i^T$) is thus affected by two forces. The first element ($s_k^T \alpha_k$) captures the mechanical direct effect on the share-weighted α: holding constant demand, the expenditure share on good k declines simply because the price of that good declined. The second element ($s_k^T \Sigma \alpha_i w_i^T$) captures how the share-weighted α changes due to the demand responses of all goods (including k) to the price change.

To see the intuition of this lemma, consider then a positive technical change to sector k inducing a decline in P_k, which we denote as $\widehat{P}_k < 0$. The condition in this lemma becomes:

$$\widehat{P}_k s_k^T \alpha_k - \widehat{P}_k s_k^T \Sigma \alpha_i w_i^T < 0 \tag{7}$$

The mechanical direct effect, $\widehat{P}_k s_k^T \alpha_k$, is always negative – prior to any change in demand, the price decline leads to a decline in the expenditure share in good k. Hence, for the condition in Lemma 2 to hold, the demand effect ($\widehat{P}_k s_k^T \Sigma \alpha_i w_i^T$) cannot be too negative.

To delve deeper into the interplay between the αs and the substitution patterns in determining the skill-premium elasticity, Corollary 1 summarizes the case where all goods are complements.[3]

Corollary 1. *Assume that the denominator in (6) is negative and all goods are gross-complements. Then: $\eta_{W^H/W^L,A_k}$ will be positive when the lowest skill intensity sector ($max(\alpha_i)$) experiences positive technical change, and negative when the highest skill intensity sector ($min(\alpha_i)$) experiences positive technical change.*

When all goods are complements, $w_i^T > 0, \forall i$, i.e. all weights in Lemma 2 are positive. As such, when the sector experiencing the positive technical change has the highest α, $\alpha_k > \Sigma_i \alpha_i w_i$ and so (7) always holds. Put differently, in this situation the direct effect always dominates. Intuitively, when all goods are complements, positive technical change to a sector increases demand for all other sectors. Therefore, a positive technical change to the lowest-skill sector (highest α_i), shifts demand *away* from this sector, thereby increasing overall demand for high-skilled labor in the economy. This reduces the equilibrium share-weighted α in the economy, and increases the skill-premium, as stated in the corollary. The reverse holds for the lowest α.[4]

Corollary 1 discusses the impact of complementary between goods. However, as discussed above, in general the effect of technical change on the share-weighted α and on the skill premium elasticity will depend on the degree to which sectors are either substitutes or complements to the sector experiencing the productivity change. Consider for example the case of the highest α sector again, but without assuming that all goods are complements. Under which conditions is the skill premium elasticity negative? From (7), for this to occur it is sufficient that $\alpha_k < \Sigma_i \alpha_i w_i$, i.e. that there exists at least one sufficiently large w_i. Following Corollary 1, this cannot occur when all goods are gross-complements and hence all $w_i \in [0,1]$, implying that in order to have a sufficiently large w_i it is necessary that at least some of the weights (w_i) are negative, i.e. some goods are substitutes. Let's consider a prime example where this can happen. Suppose that good k with the highest α is also very elastic, with $\eta_{c_k,P_k} < -1$. This implies that when P_k declines, the share

[3] This is relevant for many preference specifications. See, for example, the preferred estimates of the non-Homothetic CES preferences in Comin, Lashkari and Mestieri (2021).

[4] With further restrictions on preferences, these results extend beyond the highest and lowest α sectors. Indeed, if preferences are Non-homothetic CES and all goods are gross-complements (as in Comin, Lashkari and Mestieri (2021)), there exist $\overline{\alpha} > \underline{\alpha}$ such that:

$$\forall \alpha_k > \overline{\alpha}: \; \eta_{W^H/W^L,A_k} > 0$$
$$\forall \alpha_k < \underline{\alpha}: \; \eta_{W^H/W^L,A_k} < 0$$

Furthermore, if preferences are homothetic CES and all goods are gross-complements, then $\overline{\alpha} = \underline{\alpha}$.

of good k increases, in which case it can be shown that $w_k > 1$. Because the weights must sum to 1, this in turn implies that there must exist at least one good with a negative w_k – i.e. a good which is substitutable with good k. In such a case, the decline in P_k implies an increase in demand for the low-skilled good k, and thus an increase in the share-weighted α and a decrease in the skill-premium.

3.3. Taking Stock

To summarize, this section provides an analytic framework that characterizes the distributional impact of sectoral technical change and its underlying mechanisms. We started by showing in Theorem 1 that the distributional welfare effects are driven by two components – the Engel effect and the impact of sectoral technical change on the skill premium. The price effect is driven by the non-homotheticities and the resultant differential expenditure shares of high- and low-skilled individuals. Engel curves will thus play an important role in determining the size of this effect. Theorem 2 highlights that the skill premium's impact stems from the change in the share-weighted α. Meanwhile, Theorem 3 emphasizes the role of consumption price elasticities in shaping this share-weighted α (through changes in demand), which in turn influences both the skill premium and the welfare distribution.

4. Taking the Model to the Data

In the previous section we characterized analytically the distributional impact of sectoral technical change. Notably, Theorems 1 and 3 have another important implication: they provide a framework to assess the welfare effects of sectoral productivity changes by estimating key preference and production parameters, thereby circumventing the need for assuming specific functional forms.

As implied by our analytical approach, the set of parameters required for estimation fall into two broad categories – one pertaining to consumption and the other to production. On the consumption side we need to estimate for both high and low-skilled workers: (1) aggregate expenditure shares, (2) expenditure shares by good categories, (3) the matrix of uncompensated elasticities of consumption goods w.r.t prices, and (4) the Engel elasticities. On the production side, we need to estimate for each category (1) the equilibrium labor shares, and (2) the elasticity of substitution of the N production functions. Finally, we need to measure for each category its specific technical change.

In what follows, we discuss the empirical strategy for obtaining these parameters.

4.1. Estimation Framework

4.1.1. Consumption parameters

Given our analytical results, we do not need to constrain our analysis to a particular utility function and instead estimate an almost ideal demand system (AIDS) following Deaton and Muellbauer (1980). We can then recover the required price and income elasticities from this flexible estimated demand system. In contrast, committing to a particular utility function would involve the cost of placing restrictions on price and income elasticities, which we have shown are key in determining the welfare impact of sectoral technical change.

4.1.2. Production parameters

The first set of production parameters consist of the equilibrium labor shares by good categories. As we describe below, we measure these good-category labor shares directly from the data using industry-level labor shares and a mapping between good-categories and industries. The second set of production parameters are the sectoral elasticity of substitutions.

4.2. Data

For the consumption side of the data we use the Consumer Expenditure Survey (CEX). The CEX is a dataset produced by the U.S. Bureau of Labor Statistics that provides detailed information on the spending habits, income, and household characteristics of U.S. consumers. It is commonly used as a primary source of information for understanding and analyzing patterns of consumer expenditures. We use the dataset provided by Comin, Lashkari and Mestieri (2021), and keep their sample of urban households with a present household head aged between 25 and 64 for the years 1999-2010 and four CEX interviews.[5] We further drop households with extreme shares in a product category. We define low- and high-skilled workers in the CEX based on the household head's education level, with high-skilled defined as those with a BA degree or above.

As in Comin, Lashkari and Mestieri (2021) we combine the CEX data with regional quarterly price series by consumption category from the BLS's urban CPI (CPI-U). To aggregate prices for

[5]Their data construction is based on Aguiar and Bils (2015).

a given good category, we use region-by-quarter aggregate expenditure shares.

Our analysis requires income shares at the goods-category level. To obtain these data, we first calculate income shares by skill at the industry level using earnings data from the Current Population Survey (CPS) over the years 1999-2010. We then use an input-output matrix to map industry cost shares to consumption category cost shares (similar to Bils, Klenow and Malin (2013)).[6] To obtain the income share of a given goods-category, we calculate the weighted-average of the income shares of the industries associated with this goods-category, with the weights equal to the input costs. Appendix Table A1 reports the descriptive statistics for our sample.

Finally, we use KLEMS U.S. data on industry-level Total Factor Productivity (TFP). We aggregate these TFP measures to a goods-category measure of TFP using an analogous process to that described for income shares.

5. Quantitative Analysis

In what follows we report the results from two quantitative analyses. In each we estimate the required underlying set of preferences and production function parameters as outlined in Section 3. We then use the results from the analytical analysis to calculate the distributional welfare impact of sectoral productivity changes.

The first analysis examines the welfare consequences of sectoral productivity changes using the consumption categorization employed in the structural transformation literature (e.g. Buera and Kaboski (2012) and Comin, Lashkari and Mestieri (2021)). As in this literature, we aggregate consumption to three broad categories–Agriculture, Manufacturing and Services–and estimate the underlying price and income elasticities using an AIDS.

Given our interest in sectoral technical changes, there is a concern that a three-sector categorization is too coarse and does not adequately capture substitution patterns between goods. Hence, in our second analysis, we extend the number of sectors, looking at a finer categorization. This finer categorization naturally gives rise to more complex substitution patterns, which the AIDS formulation easily captures.

[6] Appendix A.2 describes the data construction process in more detail.

5.1. Three Sectors Case

Theorem 3 shows that estimating the distributional impact of sectoral change requires recovering price and income elasticities. To do so we estimate an AIDS to recover the required elasticities. To maintain comparability to the structural transformation literature we estimate the demand system using similar controls and instruments as in Comin, Lashkari and Mestieri (2021). The controls include household age (by age groups), household size, and number of earners. Household expenditures are instrumented with after-tax annual household income and the income quintile of the household. Regional prices for each goods-category are instrumented using the average price of the good in the other regions, weighting these prices by the goods' regional expenditure share in the households' region. See Appendix A.2 for more detail.

We thus estimate separately the vectors of parameters of the demand system ($\boldsymbol{\theta} : \boldsymbol{\gamma}, \boldsymbol{\beta}_0, \boldsymbol{\beta}, \boldsymbol{\delta}$) for the low- and high-skilled types $T \in \{H, L\}$ using a standard AIDS specification:[7]

$$s_{i,j} = \beta_i^T + \boldsymbol{\gamma}_i^{T\prime} \log \mathbf{P}_j + \delta_i^T \left[\log C_j - b\left(\log \mathbf{P}_j, \boldsymbol{\theta}^T \right) \right] + u_{i,j}$$
$$b\left(\log \mathbf{P}_j, \boldsymbol{\theta}^T \right) = \boldsymbol{\beta}_0^{T\prime} \mathbf{X}_j + \boldsymbol{\beta}^{T\prime} \log \mathbf{P}_j + 0.5 \log \mathbf{P}_j^{\prime} \boldsymbol{\Gamma}^T \log \mathbf{P}_j,$$

where there is an equation i for each sector, $s_{i,j}$ stands for the expenditure share of good i for household j in a specific period, $\mathbf{P}_j$ is the vector of goods prices, and $\mathbf{X}_j$ are household level controls.

The Differential Welfare Effects of Sectoral Technical Changes

Figure 1 provides a first look at the differential welfare impact of sectoral technical change. For each of the three sectors – Services, Manufacturing, and Agriculture – the figure depicts the percent difference in the welfare effect between high- and low-skilled workers. For example, the figure shows that a positive technical change in manufacturing leads to an approximately 20% greater welfare increase for high-skilled workers compared to low-skilled workers.

There are two key messages to the figure. First, technical change affects welfare of high and low-skilled workers differently. Second, this differential effect between high and low skilled

[7] We use the package provided by Lecocq and Robin (2015), and use block bootstrap to obtain clustered standard errors at the household level. Following Banks, Blundell and Lewbel (1997) we also check the robustness of our results allowing for quadratic Engel curves. Our results remain similar – see Appendix A.2.

workers varies across sectors in both magnitude and sign. In fact, while positive technical change in manufacturing leads to a 20% greater welfare increase for high-skilled workers, in Agriculture this number is about 40%, while in contrast, technical change in the Service sector benefits low-skilled workers more than high-skilled workers.

Decomposing the Differential Welfare Effects

Theorem 1 of Section 3 allows us to decompose the differential welfare change, $\Delta\eta_{EV,A_k}$, into its two underlying components – the Engel effect and the change in welfare stemming from the change in the skill premium. The results are shown in Figure 2.

Panel A depicts the three industries according to two attributes: their degree of low skill intensity, α, and their Engel elasticity. As implied by Section 3 and as will be discussed further shortly, these two attributes are directly linked to the channels underlying the welfare analysis: (1) **the Engel elasticity** determines the difference in expenditure shares between high- and low-skilled workers. Higher Engel elasticities imply that the difference in expenditure shares between high and low-skilled workers is larger (i.e., $s_H - s_L$ rises), which means that the Engel effect stemming from positive technical change will rise. (2) **The relative skill intensity of each sector**. As shown in Section 3, the relative skill intensity of a sector, α, plays an important role in determining the skill premium elasticity.

Panels B, C, and D of the figure depict the decomposition of the welfare impact of technical change into the Engel effect and the skill premium elasticity for Services, Manufacturing, and Agriculture respectively. Following Equation 3, the decomposition is conducted as follows:[8]

$$\Delta\eta_{EV,A_k} = (s_k^H - s_k^L) + \eta_{W^H/W^L,A_k}\left\{1 + \Sigma_i \alpha_i \left(s_i^H - s_i^L\right)\right\}. \qquad (8)$$

The Engel Effect

Consider first technical change in the Manufacturing and Agricultural sectors, depicted in Panels C and D. These are necessity sectors (Engel elasticity is smaller than one) and are low-skill intensive relative to the average in the economy. Because they are necessity sectors, expenditure shares

[8] We note that quantitatively the covariance term is negligible, given the fact that it is comprised of a product of share differentials times another share (the skill intensity). Hence in what follows, references to the skill premium elasticity disregard this covariance term. Results remain almost identical given the small magnitude of the covariance term.

of low-skilled workers are higher than that of high-skilled workers. As such, when these sectors experience a positive technical change, the associated price decrease benefits low skill workers by more. This is reflected in the negative Engel effect in panels C and D. In contrast to Manufacturing and Agriculture, Services is a luxury sector. In this sector expenditure shares of high-skilled workers are thus higher than that of low-skilled workers, implying that the Engel effect of technical change in this sector benefits high-skilled workers relatively more (a positive Engel effect in Panel B).

The Skill Premium Effect

Turning to the effect of technical changes on the skill-premium, consider first a positive productivity change in the Agriculture sector, which lowers its relative price. Panel D shows that in this case the skill-premium rises, thereby benefiting the high-skilled workers more than the low-skilled. To understand why this occurs, note that Agriculture is the sector with the lowest intensity of high-skilled workers (i.e., the highest α sector). If both Manufacturing and Services are complements to Agriculture, then following the results in Corollary 1, the skill premium must rise. As explained above, when the Agriculture price declines as a results of the productivity change, complementarities imply that demand will shift towards Manufacturing and Services – the more high-skilled intensive sectors – increasing the relative demand for high skilled workers. Now, as reported in Appendix Table A2 while Services and Agriculture are indeed estimated to be complements, there is evidence for substitution between Manufacturing and Agriculture. This makes the sign of the effect on the skill-premium an empirical question. However, because Services is the dominant sector in the economy, and because it is complement to Agriculture, it is not surprising that the skill premium rises consistent with the case where all sectors are complements. Indeed, when plugging in our estimates in the numerator of Equation 3, the price elasticity stemming from services together with its large consumption share swamps their counterparts stemming from Manufacturing.

Turning to the sector at the opposite extreme of skill intensity – Services (the high-skill intensity sector) – the predicted results are unambiguous. This is because we estimate complementarity between Services and both of the other two sectors (see Appendix Table A2). Because Services are the highest-skill intensive sector (lowest α), Corollary 1 directly implies that the skill premium must decrease, as indeed shown in Panel B.

Finally, the skill intensity of Manufacturing lies between that of Services and that of Agriculture, but overall higher when compared to the mean in the economy. As panel C shows, the effect of a price decline due to technical change in this sector on the skill-premium is positive. As discussed above, it is the estimated complementarity between Services (the largest sector in the economy) and Manufacturing that is responsible for the increase in the skill premium.

Taken together, Panels B through D show that the skill premium effect is the dominant force in determining the overall distributional impact of technical change. Across the three sectors, in absolute value, the relative magnitude of the skill premium effect is on average almost five times that of the direct effect.

Further, the results show that the skill premium effect is larger than the *total* effect of technical change; this is because in the three sector case, the Engel effect is always in the opposite directions to the skill premium effect. This, in turn, is explained by the fact that these three sectors lie in quadrants two and four in the α-Engel space. As we show below, once we examine sectors using a more disaggregated goods-category classification, sectors will appear in other quadrants as well – implying that the skill premium and direct effects are not always in opposite directions.

5.2. Extending the Number of Sectors

Given our interest in sectoral technical changes, we extend out analysis to seven sectors to adequately capture substitution patterns between sectors. This finer categorization naturally gives rise to more complex substitution patterns, which the AIDS formulation easily captures.

The Differential Welfare Effects of Sectoral Technical Changes

Panel A of Figure 3 depicts the seven sectors based on their degree of high skill intensity, α, and their Engel elasticity. Panel B of the figure shows the distributional welfare impact of technical change, decomposing the overall effect into the Engel effect and the skill premium effect.

The figure provides several key takeaways. First, focusing on the total effect, we see a differential effect of technical change on the welfare of high- versus low-skilled workers, as in the case of three sectors. In fact, in three of the seven sectors, technical change benefits low-skilled workers relatively more, while in the other four sectors, technical change benefits more the high-skilled workers. Second, the differential welfare effect of positive technical change varies in magnitude across sectors, ranging between a 20% smaller welfare increase for high-skilled workers as compared to low-skilled workers to a 70% larger welfare increase for the high-skilled.

Third, while overall the skill premium effect remains the driving force in explaining the total welfare effect, with this finer category classification, the direct effect plays a sizeable role. In fact, in two of the seven sectors (Transportation and Other Services) the direct effect is in opposite direction to the skill premium effect and dominates it. This larger direct effect is in the spirit of Jaravel (2021*b*) which shows that with finer goods categorization, there are more pronounced differences between expenditure shares across income groups.

Finally, our findings point to a general pattern whereby low-skilled (high-α sectors) exhibit positive skill premium effects, while high-skilled, low-α sectors exhibit negative skill premium effects. This is similar to the pattern exhibited in the three sector case, suggesting that complementarities are the dominant pattern in the data. In fact, as shown in Appendix Tables A3 and A4, for low skilled workers our point estimates show that approximately 66% of the cross price elasticities are negative (i.e. complement goods) while for the high-skilled this number is 55%.

The Overall Effect of TFP Changes: 1987-2019

In the prior section, we analyzed the differential welfare elasticities to sectoral technical change and showed that there is a significant variation in the magnitude of these elasticities. It is therefore of interest to calculate the overall differential welfare impact on high- versus low-skilled workers given the empirical changes in sectoral TFP observed in the data. Panels A and B of Figure 4 exhibit the wide dispersion in TFP growth over the period 1987-2019 in the seven sectors analysed in section 5.2 together with the estimated differential welfare elasticities (which we show again for convenience). Incorporating realized TFP growth in each sector together with the sectoral differential welfare elasticities, high-skilled workers enjoyed an overall 8.35% greater welfare increase compared to low-skilled workers. This value aggregates offsetting effects, with some TFP changes benefiting the high- and others benefiting the low-skilled workers.

6. Sectoral Demand Shifters

In this section, we demonstrate the versatility of our framework, emphasizing its application beyond the analysis of the welfare impact of sectoral technical change. Specifically, we explore the counterpart of supply changes—exogenous sectoral demand shifters.

We start by examining the variation in the elasticity of welfare with respect to the sectoral demand shifter across types. Let β_k denote the demand shifter for sector k. Appendix A.1.1 shows this is given by

$$\Delta\eta_{EV,\beta_k} = \frac{EV^H}{\widehat{\beta_k}} - \frac{EV^L}{\widehat{\beta_k}} = \eta_{W^H/W^L,\beta_k}\left\{1+\Sigma_i\alpha_i\left(s_i^H - s_i^L\right)\right\}. \tag{9}$$

Contrasting with Equation (3), it is apparent that the Engel effect is absent. This is because unlike in the case of productivity changes, demand shifters have no direct effect on the price; They affect prices only indirectly through changes in the composition of demand for the different sectors in the economy. The distributional effects of this indirect channel are captured in the impact of the demand shifters on the skill premium.

Hence, the focal point is the elasticity of the skill premium with respect to the sectoral demand shifter, $\eta_{W^H/W^L,\beta_k}$. In Appendix A.1.1 we further show that Equation 4 (which encompasses all equilibrium conditions in the case of sectoral technical change) can be reformulated as

$$\mathscr{H}(\beta, \frac{W_H}{W_L}) = 0, \tag{10}$$

where we replace the productivity vector, $\mathbf{A}$, with the vector of sectoral demand shifters, β. Then, equipped with this equation we show that

$$\eta_{W^H/W^L,\beta_k} = -\frac{\eta_{\mathscr{H},\beta_k}\left(\beta, \frac{W_H}{W_L}\right)}{\eta_{\mathscr{H},W_H/W_L}\left(\beta, \frac{W_H}{W_L}\right)} = \frac{\sum_{i=1}^N \alpha_i\left(S_L s_{i,L}\eta_{s_{i,L}\beta_k} + S_H s_{i,H}\eta_{s_{i,H},\beta_k}\right)}{G\left(\boldsymbol{\alpha}, \boldsymbol{\sigma}, S_L, S_H, \mathbf{s}_L, \mathbf{s}_H, \boldsymbol{\eta}^L_{\mathbf{C},\mathbf{P}}, \boldsymbol{\eta}^H_{\mathbf{C},\mathbf{P}}, \boldsymbol{\eta}^L_{\mathbf{C},\mathbf{W}}, \boldsymbol{\eta}^H_{\mathbf{C},\mathbf{W}}\right)}. \tag{11}$$

It is instructive to note the similarity here with Equation (6). The denominator, G, is in fact identical, since it continues to capture the required response of the skill premium in order to maintain excess demand at zero. In contrast, the numerator in Equation (6) features the share elasticities with respect to prices, which allowed for a direct estimation of price elasticities without requiring an explicit model specification. This stands in stark contrast to the current case of demand shifters. Indeed, Equation 11 features the share elasticities with respect to the sectoral demand shifter, β_k. This implies that a *specific* model for demand is a prerequisite for any quantifiable analysis – one that explicitly takes a position on how the demand shifters affect demand.

Recognizing this fundamental difference between the two cases (exogenous changes to supply and demand), in our analysis we assume that demand follows the Non-homothetic CES demand model as in Comin, Lashkari and Mestieri (2021):

$$c_k = \left(\beta_k C_t^{\varepsilon_k}\right)\left(\frac{E}{p_k}\right)^{\sigma}, \tag{12}$$

where C_t is implicitly defined as

$$\sum_{k=1}^{K}\left(\beta_k C_t^{\varepsilon_k}\right)^{\frac{1}{\sigma}} c_{kt}^{\frac{\sigma-1}{\sigma}} = 1. \tag{13}$$

As discussed above, under this preferences formulation all sectors are either complements or all substitutes. Given the prominence of complementarities in the three sector categorization, we estimate this demand system using the categorization of Section 5.1.

Our estimates on the differential welfare impact of sectoral demand change are intuitive. When a sector that is more low skill intensive experiences an increase in its demand, the skill premium declines. Because in the case of demand changes, the skill premium is the only operational channel, this directly maps into the welfare of the two groups: the welfare of the low-skill rises, while that of the high-skill decreases. In contrast, when a high-skill intensity sector experiences an exogenous increase in demand the reverse holds: the skill premium rises, increasing the welfare of the high-skilled while reducing the welfare of the low-skilled.

Quantitatively, we find that when the Agriculture or Manufacturing sectors (both low-skill intensive relative to the aggregate economy) experience a positive demand change, the low-skill welfare gain is approximately 60% of the high-skill welfare loss. In contrast, when the Services sector (high-skill intensive) experiences a positive demand change, the high-skill gain is approximately 170% of the low-skill loss.

7. Conclusion

In this paper we develop a general analytical framework that analyzes the distributional welfare implications of sectoral technical change. Through the integration of both supply-side and demand-side heterogeneity into our model, we show that the distributional welfare impact of sectoral technical change can be decomposed to two effects: the "Engel effect" and the "Skill Premium effect." The former is driven by non-homothetic consumption patterns, wherein consumers at varied income levels allocate their expenditure differently across goods, leading to differential gains when prices change due to sectoral productivity changes. The Skill Premium effect is driven by how sectoral technical changes shift the composition of demand across sectors; The patterns of consumption substitution and their interaction with skill intensities across sectors significantly shape the magnitude of this effect.

In terms of model primitives, the framework identifies four central factors that influence the distributional welfare impact following a sectoral technical change: (i) income elasticities of consumption goods, (ii) consumption substitution patterns, (iii) shares of different consumption sectors, and (iv) the relative skill intensity of the sector experiencing the productivity change. These are all objects that can be estimated in the data, allowing us to quantify the welfare effects of sectoral technical change.

Drawing from the Consumer Expenditure Survey (CEX), Current Population Survey (CPS), and KLEMS data, our quantitative results reveal significant welfare disparities between high- and low-skilled workers as a consequence of sectoral technical changes. In particular, the differential welfare effect between high- and low-skilled workers ranges between negative 20% and positive 70%, depending on the sector experiencing the productivity change. Moreover, our findings emphasize the prominence of the Skill Premium effect in influencing the overall distributional impact of technical change.

Finally, we note that the framework possess broad applicability and can be employed across a wide range of scenarios. While our main exploration revolves around the impact of sectoral technical changes, as one example of this versatility, we also study the effects of sectoral demand shifts resulting from exogenous changes in sectoral preferences. This analysis reveals, again, significant disparities in the welfare impact of such changes.

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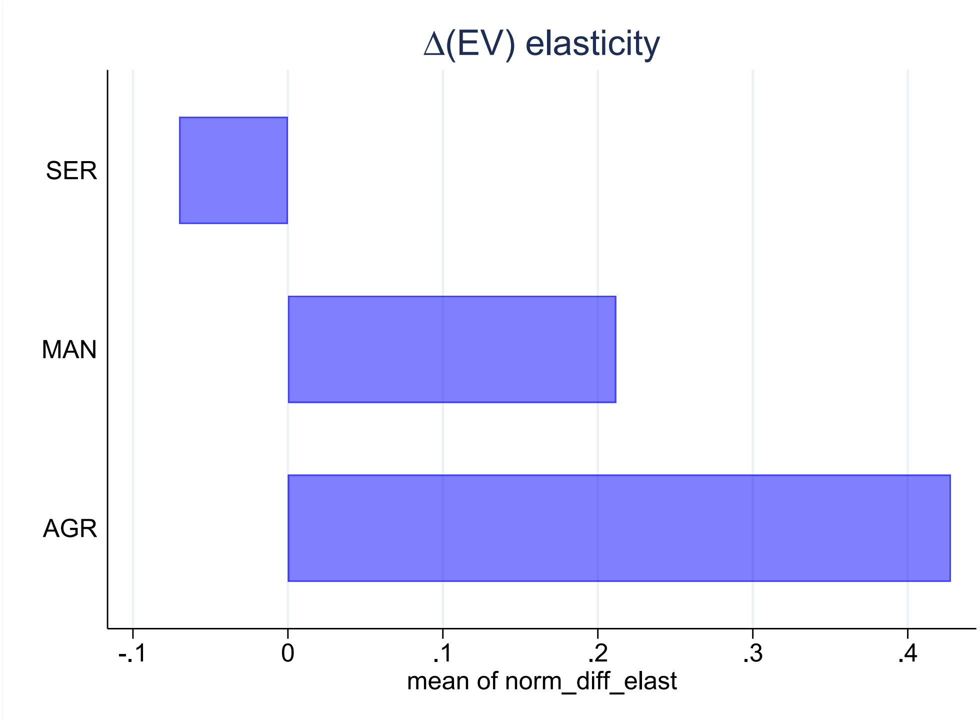
Figure 1: Differential Welfare Impact of Sectoral Technical Change



Notes: Sectors are sorted by their aggregate share. $\Delta\eta_{EV,A_k}$ is as defined in equation (3). Each bar depicts $\frac{\Delta\eta_{EV,A_k}}{\eta_{EV_L,A_k}}$

Figure 2: Decomposing the Welfare Impact of Sectoral Technical Change: 3 Sectors

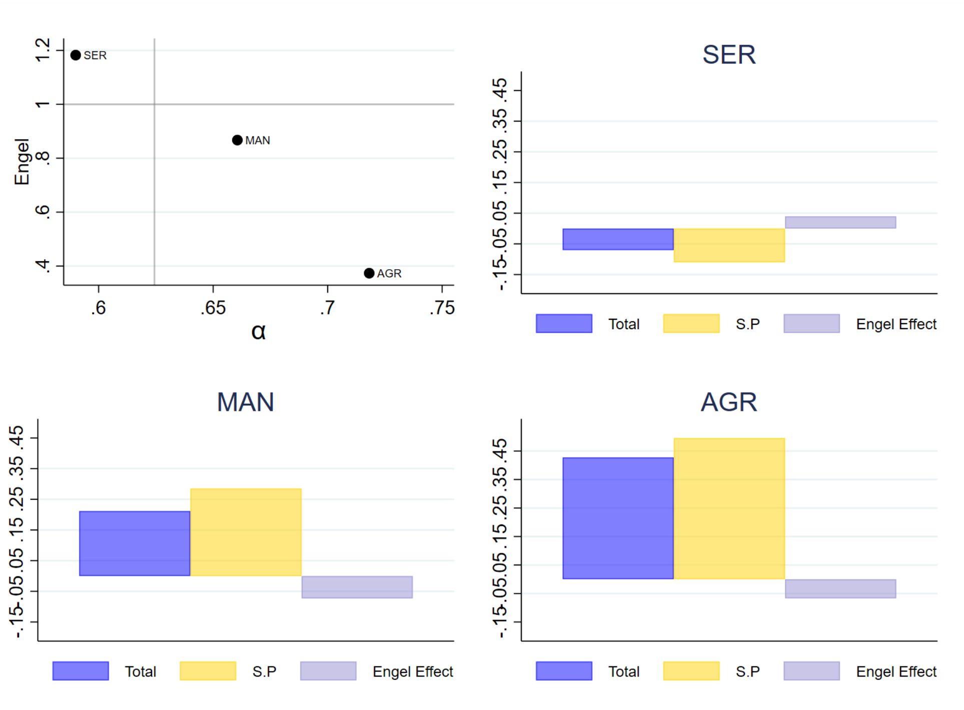


Figure 3: Decomposing the Welfare Impact of Sectoral Technical Change: 7 Sectors

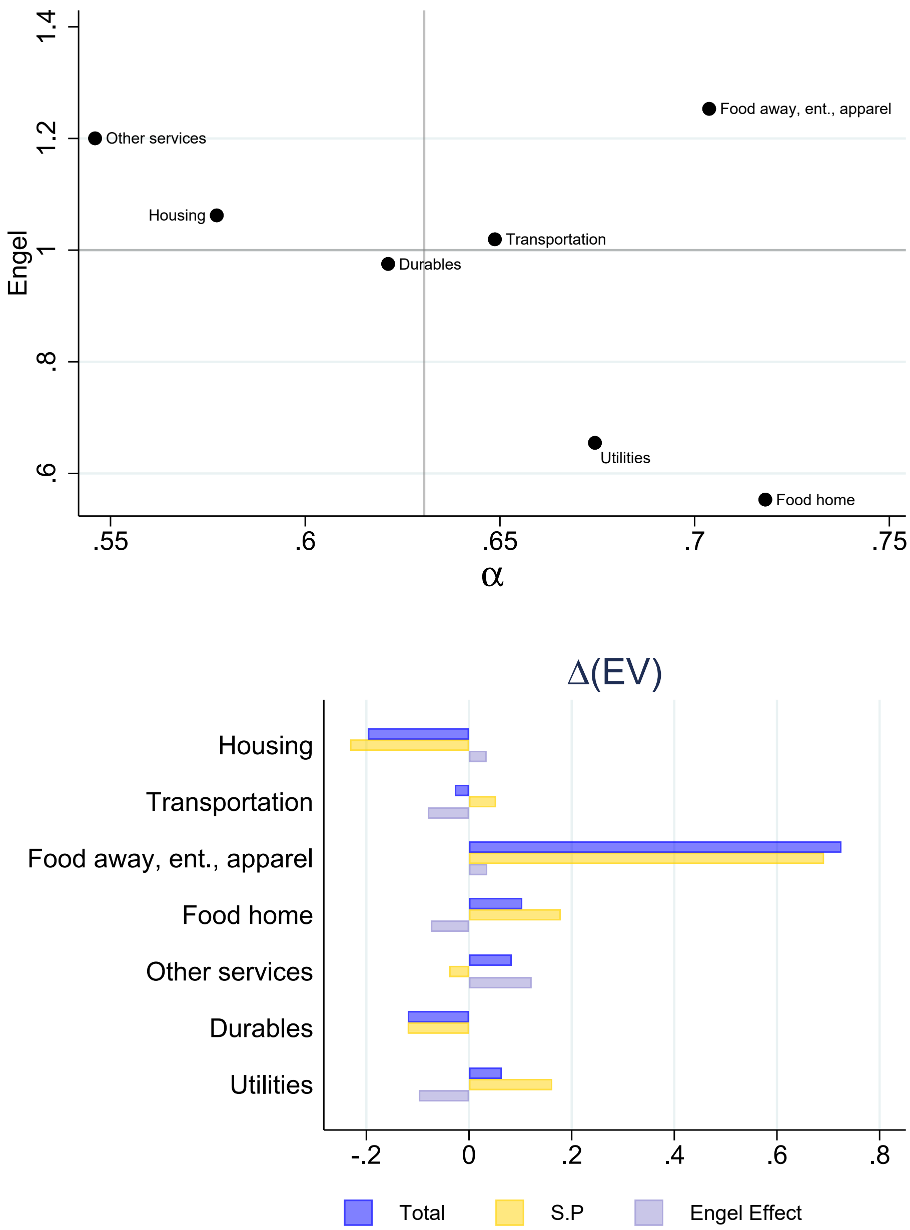
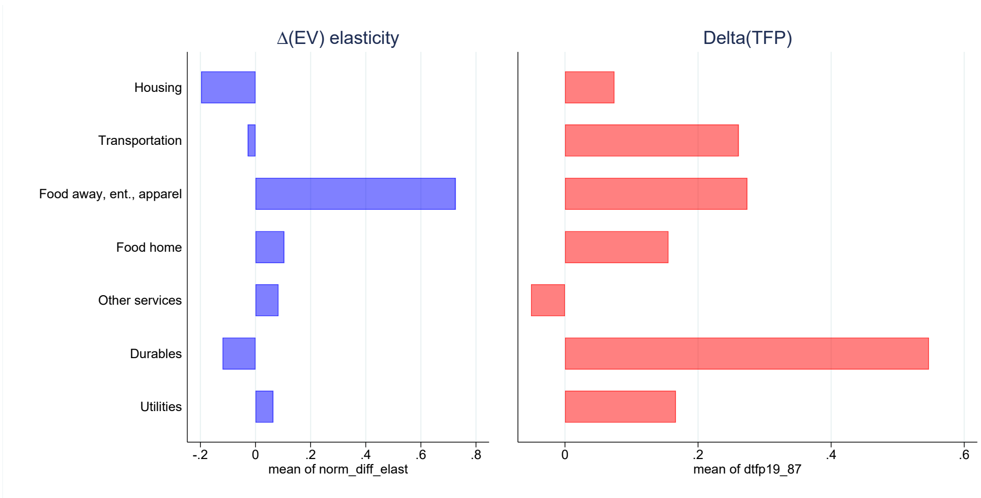


Figure 4: The Distributional Sectoral Effects of TFP Changes



A. Appendix

A.1. Theoretical Derivations

TBD

A.1.1. Theoretical Derivations: Demand Shifters

TBD

A.2. Empirical Analysis

A.2.1. Data Construction and Estimation Details

TBD

A.2.2. Appendix Tables

Table A1: Descriptive Statistics

	Low skill			High skill		Low-skille labor shar
	Mean	S.D.		Mean	S.D.	
A. Expenditure shares: 3 goods						
Agriculture	0.13	0.05	0	0.11	0.04	0.72
Manufacturing	0.27	0.09	0	0.25	0.09	0.66
Services	0.6	0.1	0	0.64	0.09	0.59
B. Expenditure shares: 7 goods						
Food home	0.13	0.06		0.11	0.05	0.72
Housing	0.35	0.11		0.37	0.11	0.58
Utilities	0.07	0.03		0.05	0.03	0.67
Transportation	0.16	0.1		0.15	0.1	0.65
Food away, ent., apparel	0.14	0.07		0.15	0.07	0.7
Other services	0.09	0.07		0.1	0.07	0.55
Durables	0.06	0.04		0.06	0.04	0.62
C. Household aggregates and controls						
Nominal household expenditures	37,644	20,188		48,420	25,716	
Nominal household after tax income	53,578	29,974		73,766	35,792	
Age	45.5	10.4		44.3	10.5	
Number of family members	3	1.5		2.7	1.4	
A two earner household	0.6	0.5		0.6	0.5	
Number of households	18,045			9,226		
Number of observations	56,018			29,509		

Notes: Descriptive Statistics for CEX sample used in the estimation of the AIDS.

Table A2: Expenditure and price elasticities: 3 categories

A. Low-skilled:

	Expenditure Elasticity	Price Elasticities		
		Agriculture	Manufacturing	Services
Agriculture	0.332***	-0.274*	0.431***	-0.489***
	(0.016)	(0.151)	(0.038)	(0.127)
	[0.307,0.36]	[-0.523,-0.019]	[0.373,0.493]	[-0.704,-0.282]
Manufacturing	0.874***	0.128***	-0.52***	-0.482***
	(0.017)	(0.017)	(0.035)	(0.03)
	[0.848,0.902]	[0.1,0.154]	[-0.575,-0.466]	[-0.538,-0.436]
Services	1.194***	-0.207***	-0.306***	-0.682***
	(0.008)	(0.026)	(0.014)	(0.027)
	[1.177,1.203]	[-0.248,-0.16]	[-0.329,-0.282]	[-0.726,-0.637]

B. High-skilled:

	Expenditure Elasticity	Price Elasticities		
		Agriculture	Manufacturing	Services
Agriculture	0.442***	-0.579***	0.399***	-0.262
	(0.026)	(0.21)	(0.059)	(0.176)
	[0.394,0.482]	[-0.914,-0.243]	[0.31,0.501]	[-0.504,0.053]
Manufacturing	0.856***	0.135***	-0.404***	-0.587***
	(0.03)	(0.027)	(0.043)	(0.046)
	[0.812,0.908]	[0.091,0.18]	[-0.462,-0.311]	[-0.689,-0.533]
Services	1.163***	-0.134***	-0.317***	-0.712***
	(0.013)	(0.033)	(0.02)	(0.033)
	[1.138,1.184]	[-0.181,-0.077]	[-0.357,-0.289]	[-0.753,-0.652]

Notes: Expenditure and uncompensated price elasticities implied by the AIDS estimates. Bootstrapped standard errors in parentheses, and 90% confidence intervals in square brackets.

Table A3: Expenditure and price elasticities: 7 categories, low-skilled

	Expenditure Elasticity	Price Elasticities						
		Food home	Housing	Utilities	Transportation	Food away, ent., apparel	Other services	Durables
Food home	0.524***	-0.673***	-0.355*	0.236***	-0.091	0.028	0.109	0.221***
	(0.011)	(0.255)	(0.189)	(0.078)	(0.08)	(0.175)	(0.066)	(0.064)
	[0.508,0.542]	[-1.081,-0.238]	[-0.661,-0.048]	[0.11,0.357]	[-0.221,0.033]	[-0.237,0.306]	[-0.001,0.228]	[0.127,0.334]
Housing	1.046***	-0.199***	-0.374***	-0.085***	0.035	-0.418***	-0.032	0.029
	(0.009)	(0.07)	(0.114)	(0.032)	(0.042)	(0.059)	(0.042)	(0.03)
	[1.031,1.06]	[-0.313,-0.088]	[-0.55,-0.19]	[-0.132,-0.026]	[-0.044,0.098]	[-0.516,-0.334]	[-0.102,0.039]	[-0.012,0.082]
Utilities	0.664***	0.45***	-0.323*	-0.734***	0.051	-0.065	0.053	-0.096
	(0.012)	(0.155)	(0.169)	(0.088)	(0.088)	(0.128)	(0.064)	(0.075)
	[0.645,0.683]	[0.203,0.691]	[-0.569,-0.009]	[-0.881,-0.594]	[-0.106,0.184]	[-0.293,0.15]	[-0.048,0.152]	[-0.219,0.029]
Transportation	1.06***	-0.141**	0.069	-0.006	-0.775***	-0.028	-0.102**	-0.078**
	(0.014)	(0.063)	(0.089)	(0.035)	(0.079)	(0.057)	(0.045)	(0.033)
	[1.036,1.083]	[-0.243,-0.045]	[-0.09,0.205]	[-0.069,0.046]	[-0.888,-0.626]	[-0.122,0.069]	[-0.179,-0.029]	[-0.132,-0.026]
Food away, ent., apparel	1.245***	-0.067	-1.104***	-0.068	-0.063	0.33**	-0.059	-0.214***
	(0.012)	(0.161)	(0.145)	(0.059)	(0.067)	(0.155)	(0.073)	(0.058)
	[1.222,1.265]	[-0.312,0.192]	[-1.348,-0.895]	[-0.174,0.032]	[-0.172,0.051]	[0.091,0.591]	[-0.16,0.07]	[-0.315,-0.124]
Other services	1.269***	0.062	-0.204	0	-0.222***	-0.096	-0.883***	0.074
	(0.019)	(0.096)	(0.164)	(0.047)	(0.084)	(0.114)	(0.12)	(0.053)
	[1.235,1.302]	[-0.096,0.237]	[-0.475,0.071]	[-0.075,0.073]	[-0.362,-0.09]	[-0.254,0.107]	[-1.082,-0.684]	[-0.009,0.158]
Durables	0.986***	0.392***	0.179	-0.119	-0.191**	-0.438***	0.129*	-0.938***
	(0.014)	(0.131)	(0.166)	(0.077)	(0.086)	(0.127)	(0.074)	(0.075)
	[0.961,1.007]	[0.199,0.615]	[-0.043,0.48]	[-0.246,0.009]	[-0.334,-0.056]	[-0.661,-0.238]	[0.012,0.247]	[-1.052,-0.801]

Notes: Expenditure and uncompensated price elasticities implied by the AIDS estimates. Bootstrapped standard errors in parentheses, and 90% confidence intervals in square brackets.

Table A4: Expenditure and price elasticities: 7 categories, high-skilled

	Expenditure Elasticity	Price Elasticities						
		Food home	Housing	Utilities	Transportation	Food away, ent., apparel	Other services	Durables
Food home	0.603***	-0.525*	-0.181	-0.125	0.122	0.152	0.092	-0.138*
	(0.014)	(0.315)	(0.238)	(0.082)	(0.087)	(0.214)	(0.083)	(0.073)
	[0.58,0.626]	[-0.996,0.017]	[-0.557,0.216]	[-0.26,-0.006]	[-0.006,0.284]	[-0.198,0.489]	[-0.031,0.227]	[-0.261,-0.014]
Housing	1.09***	-0.119	-0.393***	-0.015	-0.078	-0.613***	0.019	0.108***
	(0.012)	(0.079)	(0.128)	(0.034)	(0.055)	(0.076)	(0.059)	(0.035)
	[1.069,1.109]	[-0.246,0.017]	[-0.585,-0.178]	[-0.069,0.041]	[-0.171,0.013]	[-0.741,-0.494]	[-0.089,0.101]	[0.047,0.159]
Utilities	0.639***	-0.257	0.074	-0.668***	0.039	0.383**	0.055	-0.264***
	(0.018)	(0.167)	(0.208)	(0.111)	(0.111)	(0.177)	(0.089)	(0.101)
	[0.606,0.667]	[-0.532,-0.014]	[-0.248,0.412]	[-0.85,-0.49]	[-0.141,0.221]	[0.113,0.689]	[-0.08,0.209]	[-0.434,-0.1]
Transportation	0.95***	0.055	-0.135	-0.003	-0.733***	0.066	-0.231***	0.031
	(0.023)	(0.069)	(0.132)	(0.044)	(0.114)	(0.085)	(0.072)	(0.051)
	[0.912,0.989]	[-0.043,0.185]	[-0.375,0.072]	[-0.075,0.067]	[-0.928,-0.531]	[-0.063,0.202]	[-0.36,-0.116]	[-0.048,0.109]
Food away, ent., apparel	1.267***	0.046	-1.587***	0.119	0.021	0.278	-0.087	-0.057
	(0.02)	(0.176)	(0.192)	(0.072)	(0.089)	(0.189)	(0.089)	(0.07)
	[1.233,1.295]	[-0.243,0.323]	[-1.918,-1.281]	[0.01,0.246]	[-0.116,0.162]	[-0.067,0.581]	[-0.221,0.073]	[-0.164,0.063]
Other services	1.083***	0.053	0.072	0.006	-0.371***	-0.1	-0.721***	-0.022
	(0.033)	(0.1)	(0.212)	(0.053)	(0.109)	(0.129)	(0.162)	(0.062)
	[1.035,1.139]	[-0.098,0.216]	[-0.332,0.362]	[-0.078,0.098]	[-0.559,-0.202]	[-0.293,0.129]	[-0.971,-0.42]	[-0.115,0.105]
Durables	0.957***	-0.306**	0.67***	-0.268***	0.074	-0.088	-0.022	-1.017***
	(0.023)	(0.138)	(0.203)	(0.096)	(0.124)	(0.162)	(0.098)	(0.116)
	[0.918,0.995]	[-0.545,-0.069]	[0.314,0.965]	[-0.431,-0.11]	[-0.117,0.265]	[-0.34,0.192]	[-0.165,0.179]	[-1.212,-0.83]

Notes: Expenditure and uncompensated price elasticities implied by the AIDS estimates. Bootstrapped standard errors in parentheses, and 90% confidence intervals in square brackets.