

Of Fathers and Farms

How Intergenerational Persistence Shapes Structural Transformation

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Abstract. The transmission of skills and preferences from parents to children leads to intergenerational persistence in sector choice. How do these inherited connections alter the process of structural transformation? Using linked father–son records in census microdata, this paper establishes that both inherited skills and inherited preferences are important sources of persistence in the United States between 1880 and 1940. Embedding these findings into a macroeconomic model of structural change, the paper shows that intergenerational persistence slowed the process of U.S. industrialization by 12.8 percent. Inherited skills account for nearly all of this slowdown because their immediate and dynamic effects reinforce each other, whereas those of inherited preferences largely offset. Accounting for persistence also implies substantially greater agricultural technology growth relative to nonagriculture than a model without persistence would infer from the same historical transition.

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Introduction

Most people today know a doctor, a lawyer, or an academic who followed in their parents' footsteps. Occupational transmission is not limited to high-skilled professions; indeed, it is especially pronounced among farmers. This micro-level fact raises a macro-level question: how does intergenerational persistence in sector choice reshape the dynamics of structural transformation?

Research on structural change has typically focused on technological and demand forces that reallocate labor across sectors (Herrendorf, Rogerson and Valentinyi, 2014). Recent work has highlighted new generations of workers entering the labor force as a critical source of this reallocation (Hobijn, Schoellman and Vindas, 2018; Porzio, Rossi and Santangelo, 2022; Adão, Beraja and Pandalai-Nayar, 2024). Intuitively, a new worker may be more flexible to changing economic conditions than an incumbent who has formed strong ties through their experience in a given sector. Although new workers have no employment history of their own, they nevertheless enter the labor force connected to their parents' sectors through the skills and preferences they inherit. This paper studies how these inherited connections alter the reallocation of workers out of agriculture.

As a canonical episode of structural transformation, the United States' industrialization between 1880 and 1940 provides an ideal setting to quantify the paper's insights. Using linked father-son records from the full-count historical U.S. census microdata (Helgertz et al., 2024), I document large differences in sector choice between workers whose fathers worked in agriculture (i.e., "ag-born") and those whose fathers worked outside agriculture (i.e., "nonag-born"). These differences remain substantial after accounting for childhood school attendance and local labor markets: in 1880, ag-born workers were over 3.4 times as likely to work in agriculture as nonag-born workers. Moreover, ag-born and nonag-born workers have systematically different earnings within the same sector, suggesting that workers' productivity may also depend on their parents' sector.

Guided by these empirical patterns, I develop a two-sector macro model of structural transformation with intergenerational persistence. New workers choose between agriculture and nonagriculture based on the earnings and nonpecuniary benefits available in each sector. There are two sources of intergenerational persistence: higher productivity in their parents' sector (i.e., *inherited skills*) and nonpecuniary attachments to their parents' sector (i.e., *inherited preferences*). Inherited skills increase the earnings workers can obtain in their parents' sector, while inherited preferences make agricultural employment more appealing to ag-born workers even when they could earn more elsewhere. In the model,

structural change originates from exogenous changes in either sectoral production technologies or the nonpecuniary sectoral benefits common to all workers. I model consumer demand as in [Comin, Lashkari and Mestieri \(2021\)](#), so technological progress reallocates labor through changes in income and relative prices.

The model shows that intergenerational persistence alters how workers respond to economic changes both within and across generations. Both inherited skills and inherited preferences reduce the aggregate responsiveness of new workers to wage changes, dampening their reallocation out of agriculture. Through these inherited connections, exogenous factors pulling workers out of agriculture today also have dynamic effects on the next generation of workers. Inherited preferences reinforce the initial movement out of agriculture, whereas inherited skills can generate large enough wage adjustments to reverse it. Overall, how much intergenerational persistence accelerates or slows industrialization depends on the strength of both inherited skills and preferences.

Quantifying these effects for U.S. industrialization requires identifying the two sources of intergenerational persistence and inferring the economic forces driving the historical transition. Earnings differences between ag-born and nonag-born workers in the same sector reflect both inherited skills and gains from self-selection ([Lagakos and Waugh, 2013](#)). The model allows me to account for these selection effects using workers' sector choices and skill dispersion inferred from earnings variation within sector-by-parental-sector groups. Assuming workers face the same sectoral wages regardless of parental background, the remaining earnings differences identify inherited skills, while residual persistence in sector choice identifies inherited preferences. Finally, I infer the historical evolution of sectoral technologies and common nonpecuniary benefits by matching observed agricultural employment shares, relative prices, and real GDP per capita growth.

Using the historical microdata, I find that both inherited skills and inherited preferences are quantitatively large and important sources of intergenerational persistence. My estimates imply that ag-born workers are 50 percent more productive in agriculture while nonag-born workers are 74 percent more productive in nonagriculture. Together, inherited skills in both sectors account for 71 percent of the observed intergenerational persistence in sector choice. I attribute the remaining 29 percent of intergenerational persistence to inherited preferences. I infer that ag-born workers choose to remain in agriculture even when that implies an earnings discount equal to 32 percent of their potential nonagricultural earnings.

I conduct counterfactual simulations to quantify how U.S. industrialization would have

unfolded without inherited skills or inherited preferences. Each counterfactual economy is calibrated to match the same aggregate moments in 1880, and the simulated economies are then exposed to the same inferred growth in sectoral technologies and common non-pecuniary benefits through 1940. Removing intergenerational persistence altogether increases industrialization by 4.9 percentage points (i.e., 12.8 percent of the observed reallocation of workers into nonagriculture).¹ Inherited skills account for nearly all of this effect. Without inherited preferences, industrialization increases by only 0.8 percentage points while removing inherited skills alone increases it by 5.3 percentage points.

To understand why inherited skills account for most of the slowdown in industrialization, I distinguish between the *immediate* response of new workers to changing economic conditions and the *dynamic* effects transmitted through subsequent generations. Both inherited mechanisms reduce new workers' aggregate responsiveness to wages; in the linked 1880 U.S. sample, observed intergenerational persistence lowers this elasticity by 42 percent. After accounting for general equilibrium feedback, inherited preferences impose a slightly greater immediate constraint on reallocation than inherited skills. However, across generations, the two mechanisms have sharply different consequences. With inherited preferences, changes in parental composition lead to further reallocation out of agriculture, mostly offsetting the immediate slowdown. With inherited skills, the resulting shifts in sectoral labor productivity induce wage adjustments that instead amplify the slowdown. Thus, the immediate and dynamic effects of inherited skills reinforce each other, while those of inherited preferences largely offset each other.²

Finally, I show that accounting for intergenerational persistence changes what the model infers about the forces behind U.S. industrialization. As industrialization reduces the share of ag-born workers, inherited skills shift the supply of productive labor toward nonagriculture even without changes in sectoral technologies. Without accounting for this effect, matching the observed transition requires substantially more growth in nonagricultural relative to agricultural technology: 77.8 rather than 46.6 log points, an increase of 67 percent. Thus, parent sector dependence changes not only how workers respond to historical forces, but also the technological changes the model infers to explain the observed transition.

¹For scale, [Brandt, Hsieh and Zhu \(2008\)](#) find that improvements in rural labor mobility contributed 8 (out of 38) percentage points to China's industrialization between 1978 and 2004.

²Under alternative calibrations with modest intergenerational persistence driven primarily by inherited preferences, the dynamic effects can more than offset the immediate dampening of reallocation. In such cases, inherited preferences modestly *accelerate* structural transformation.

Literature This paper bridges two vast yet distinct literatures: research on structural transformation and research on intergenerational occupational choice. I contribute to a growing strand emphasizing the critical role of new workers for labor reallocation as well as a nascent strand highlighting the macroeconomic consequences of micro-level occupational persistence. In addition, my work yields an insight broadly relevant for research in macroeconomics and international trade that uses quantitative models of labor allocation built on extreme-value discrete choice.

Relative to the recent work showcasing the importance of new generations of workers for structural change ([Hobijn, Schoellman and Vindas, 2018](#); [Porzio, Rossi and Santangelo, 2022](#); [Adão, Beraja and Pandalai-Nayar, 2024](#)), I show that individual workers' inherited connections to their parents' sectors meaningfully alter the aggregate process of reallocation.³ Quantitative macroeconomic studies of structural change have almost exclusively abstracted from this mechanism. A prominent exception is [Hayashi and Prescott \(2008\)](#), who attribute Japan's depressed prewar output to an institutional barrier that kept agricultural employment roughly constant by forcing the designated heir to remain on the family farm. Relative to their aggregate restriction, my framework models persistence through worker-level sector choices and allows it to arise from either inherited skills or preferences, which I discipline using microdata. Crucially, I show that these two mechanisms have very different implications for structural transformation.

There is a very large literature measuring intergenerational persistence in occupation choice and evaluating specific determinants ([Abramitzky, Boustan and Matiashvili, 2025](#)). I contribute to a growing set of studies that focus on the macroeconomic consequences of this micro-level persistence.⁴ [Cassan, Keniston and Kleineberg \(2021\)](#), [Lo Bello and Morchio \(2022\)](#), and [Almgren, Kramer and Sigurdsson \(2025\)](#) develop quantitative models to distinguish the sources of intergenerational occupational persistence and evaluate their implications for the allocation of talent and aggregate welfare. In contrast, I ask how persistence alters the long-run reallocation of workers in an economy experiencing major changes in economic fundamentals.

Finally, my analytical result speaks to a broader literature in quantitative macroeconomics and international trade that studies worker reallocation with extreme-value discrete choice models ([Artuç, Chaudhuri and McLaren, 2010](#); [Caliendo, Dvorkin and Parro, 2019](#)). I show that even when different groups of workers have identical labor supply

³[Kim and Topel \(1995\)](#) and [Lee and Wolpin \(2006\)](#) also remark on new workers' role in labor reallocation.

⁴Several empirical papers focus on intergenerational persistence in agriculture and remark on the potential importance for structural change without explicitly studying it ([Emran and Shilpi, 2011](#); [Fernando, 2022](#); [Haws, Just and Price, 2025](#); [Liu, 2026](#)).

elasticities, the aggregate labor supply elasticity can be substantially lower if these groups differ in their sector choices. In my setting, intergenerational persistence generates precisely these differences between ag-born and nonag-born workers. Moreover, because the composition of these groups changes across generations, so does the aggregate responsiveness of workers to wages.⁵

Roadmap Section 1 presents the motivating evidence on intergenerational persistence in the U.S. between 1880 and 1940. Section 2 develops a general equilibrium model of structural transformation with intergenerational persistence and characterizes its implications for worker reallocation within and across generations. Section 3 establishes how workers' sector choices and earnings identify inherited skills and preferences, and how aggregate economic outcomes identify the exogenous drivers of structural transformation. Section 4 estimates the model's labor supply parameters, calibrates consumer demand, and quantifies how intergenerational persistence shaped U.S. industrialization between 1880 and 1940. Section 5 concludes.

1. Motivating Facts

In this section, I document two patterns in the historical U.S. census that motivate the model developed in the next section. First, workers whose fathers were employed in agriculture are substantially more likely to work in agriculture themselves. Second, workers' earnings within the same sector differ systematically according to their fathers' sectors of employment. Both patterns hold even after accounting for differences across local labor markets. Together, these patterns suggest that parental background shapes both workers' sector choices and the earnings they obtain within sectors, motivating a framework that distinguishes inherited skills, inherited preferences, and endogenous selection.

To document these facts, I use the full-count U.S. decennial census microdata for 1880–1940 from IPUMS (Ruggles et al., 2024). I restrict attention to U.S.-born employed men aged 20–29 with observed industry, classifying workers as agricultural if their industry is coded as agriculture by IPUMS.⁶ To identify their fathers' sectors, I link these workers to their childhood households using the IPUMS Multigenerational Longitudinal Panel

⁵Relatedly, Böhm, Etheridge and Irastorza-Fadrique (2025) examine how the mobility patterns of incumbent workers shape occupational labor supply elasticities, whereas my result emphasizes how differences in sector choice among groups of new workers shape their aggregate labor supply responsiveness.

⁶Agriculture comprises IND1950 codes 100–199.

(Helgertz et al., 2024).⁷

Sector Choices Figure 1 documents the evolution of young workers’ agricultural employment shares. Panel A shows that the share of young workers employed in agriculture fell from 61 percent in 1880 to 23 percent in 1940. Despite this large reallocation, ag-born and nonag-born workers made very different sector choices: in 1880, over 80 percent of ag-born workers were employed in agriculture, compared with less than 20 percent of nonag-born workers. Panel B summarizes this persistence as the difference in agricultural employment rates between ag-born and nonag-born workers under three specifications: without controls; with age and race fixed effects; and with age and race fixed effects plus fully interacted childhood-by-adulthood commuting-zone fixed effects.

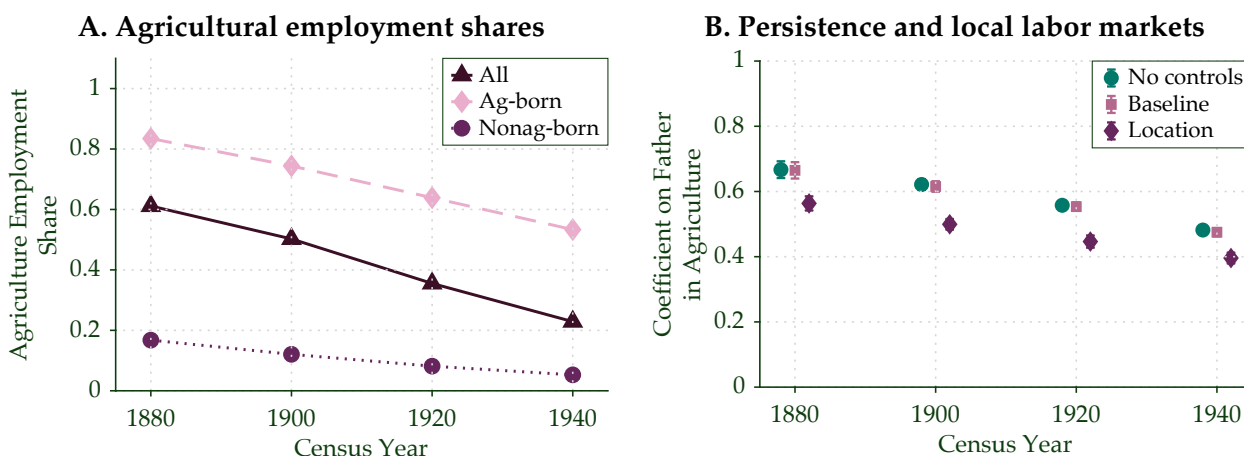


Figure 1: Agricultural Employment and Intergenerational Persistence, 1880–1940

Note: Panel A plots agricultural employment shares among linked U.S.-born employed men aged 20–29, separately for all workers, workers whose fathers were employed in agriculture (ag-born), and workers whose fathers were employed outside agriculture (nonag-born). Panel B plots coefficients on an indicator for an agricultural father from separate linear probability models of agricultural employment. The no-controls specification includes no covariates; the baseline specification includes age and race fixed effects; and the location specification additionally assigns a separate fixed effect to each observed childhood-to-adulthood commuting-zone pair. Whiskers in Panel B denote 95 percent confidence intervals from standard errors clustered by adulthood commuting zone. Agriculture comprises IND1950 codes 100–199.

The unconditional agricultural employment gap between parental groups was 66.7 percentage points in 1880 and remained 48.2 percentage points in 1940. One concern is that this gap may exclusively reflect differences across local labor markets. Put simply, if agricultural jobs are concentrated in the rural hinterland while nonagricultural jobs are con-

⁷I first link each worker to his childhood record in an earlier census and then use within-household relationships to identify his father and his father’s industry. Appendix A.1.2 establishes robustness to alternative historical census links from the Census Tree (Price, Buckles and Clement, 2021; Buckles et al., 2025) and the Census Linking Project (Abramitzky et al., 2025).

centrated in industrial cities, then ag-born workers may be more likely to work in agriculture simply because they are more likely to live in rural areas. However, Panel B shows that the gap remains large after accounting for age and race and after comparing workers within the same childhood-to-adulthood commuting-zone pair.

Earnings Parental sector predicts not only where workers are employed, but also how much they earn within the same sector. Because 1940 is the first census to report individual earnings, I focus on that year and further restrict the sample to workers with positive wage and salary income, positive weeks worked, and positive usual weekly hours. Figure 2 plots regressions of log hourly earnings on an indicator for whether a worker’s father was employed in agriculture, estimated separately for agricultural and nonagricultural workers. It reports the same three specifications as the sector-choice analysis: no controls; age and race fixed effects; and age and race fixed effects plus fully interacted childhood-by-adulthood commuting-zone fixed effects.

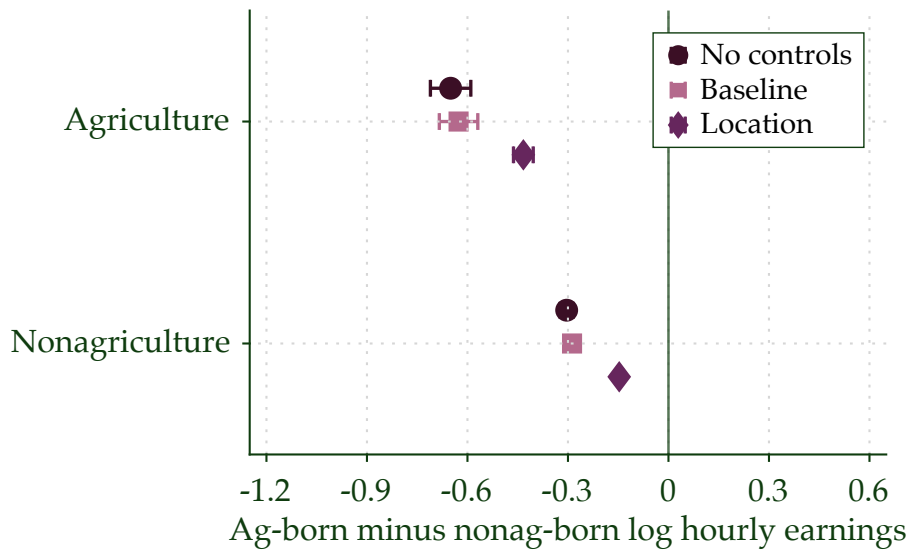


Figure 2: Earnings Differences by Parental Sector, 1940

Note: Each marker reports the coefficient on an indicator for whether a worker’s father was employed in agriculture from a separate regression of log hourly wage and salary income within the indicated destination sector; negative values therefore indicate lower earnings for ag-born workers than for nonag-born workers. The no-controls specification includes no covariates; the baseline specification includes age and race fixed effects; and the location specification additionally assigns a separate fixed effect to each observed childhood-to-adulthood commuting-zone pair. None of the specifications controls for childhood schooling; Appendix Table 9 reports the corresponding schooling sensitivity. The sample consists of linked U.S.-born employed men aged 20–29 with observed own and paternal industries, positive wage and salary income, positive weeks worked, and positive usual weekly hours. Whiskers denote 95 percent confidence intervals from standard errors clustered by adulthood commuting zone. Appendix Table 8 reports the estimates and regression diagnostics.

Without controls, ag-born workers earn approximately 48 percent less than nonag-born workers in agriculture and 26 percent less in nonagriculture. Adding age and race fixed effects yields gaps of approximately 47 and 25 percent, respectively; additionally comparing workers within the same childhood-to-adulthood commuting-zone pair narrows the gaps to approximately 35 and 14 percent, but both remain substantial. At first glance, it may seem surprising that ag-born workers earn less than nonag-born workers in agriculture, despite being much more likely to work there. On its face, this pattern may suggest that nonag-born workers are ubiquitously more productive than ag-born workers, and that ag-born workers disproportionately enter agriculture only because they are constrained or otherwise prefer to do so. However, this overlooks a potentially important selection effect: with relatively few nonag-born workers entering agriculture, they may be especially positively selected on their agricultural skills. Hence, these earnings differences could reflect both workers inheriting productive skill advantages in their parents' sectors and potent selection effects.

Together, these findings establish substantial intergenerational persistence in sector choice and systematic earnings differences by parental sector. On their own, these facts do not establish the exact sources of persistence, especially whether they reflect inherited skills or inherited preferences. The next section develops a model that distinguishes these mechanisms and traces their implications for structural transformation.

2. A Model of Structural Change with Intergenerational Persistence

I develop a two-sector general equilibrium model of structural transformation in which worker allocations are linked across generations. In each period, a new generation of workers replaces the previous one. Workers are classified according to whether their parents worked in agriculture (ag-born) or nonagriculture (nonag-born), so the composition of the labor force depends on the previous generation's sectoral allocation.

The labor supply block builds on a Roy model of comparative advantage and self-selection (Roy, 1951; Lagakos and Waugh, 2013). Workers choose between agriculture and nonagriculture based on their potential earnings and the nonpecuniary benefits of employment in each sector. I introduce two sources of intergenerational persistence: inherited skills, which raise workers' productivity in their parents' sectors, and inherited preferences, which make leaving agriculture less attractive to the children of farmers. I combine this labor supply framework with sectoral production and nonhomothetic con-

sumer demand to determine equilibrium wages and allocations. Finally, I characterize how intergenerational persistence affects workers' aggregate responsiveness to wages and the immediate and dynamic effects of technological change.

2.1. Labor Supply

There is a unit mass of households indexed by i and two sectors of production indexed by $j \in \{A, N\}$, where A and N denote agriculture and nonagriculture, respectively. Households are dynastic and workers live for a single period: the worker inhabiting household i in period $t - 1$ is the parent of the worker inhabiting household i in period t . Let $k \in \{A, N\}$ denote a worker's parental sector, and refer to workers whose parents were employed in sector k as type- k workers.

The Worker's Problem Workers draw independent sector-specific skills, $\epsilon_{i,j,t}$, from a common Fréchet distribution with cumulative distribution function $F(\epsilon) = \exp(-\epsilon^{-\gamma})$, where $\gamma > 1$ and larger values of γ imply less skill dispersion. The effective labor that worker i of type k can supply to sector j is

$$h_{i,j,t}(k) = \epsilon_{i,j,t} \cdot \kappa_j^{\mathbb{1}(k=j)},$$

where $\mathbb{1}(\cdot)$ is an indicator function and $\kappa_j \geq 1$ governs workers' inherited skill if their parent worked in sector j . For example, if $\kappa_A = 1.5$, then an ag-born worker can supply 50 percent more effective labor to agriculture than an identical nonag-born worker, but this inherited skill advantage does not carry over to nonagriculture.

Workers earn $y_{i,j,t}(k) = w_{j,t} \cdot h_{i,j,t}(k)$, where $w_{j,t}$ is the wage per efficiency unit of labor in sector j . Each sector also provides a common nonpecuniary benefit, $B_{j,t} > 0$, that affects workers' utility but not their earnings. The indirect utilities from working in agriculture and nonagriculture are

$$\begin{aligned} V_{i,A,t}(k) &= B_{A,t} \cdot w_{A,t} \cdot h_{i,A,t}(k), \\ V_{i,N,t}(k) &= B_{N,t} \cdot w_{N,t} \cdot h_{i,N,t}(k) \cdot (1 - \tau)^{\mathbb{1}(k=A)}, \end{aligned}$$

where $\tau \in [0, 1)$ captures inherited preferences that reduce the attractiveness of nonagricultural employment for ag-born workers without directly affecting their earnings. For example, if $\tau = 0.5$, an ag-born worker requires nonagricultural earnings to be twice as

high as agricultural earnings to be willing to leave agriculture, holding common sectoral nonpecuniary benefits equal.

Each worker chooses the sector that maximizes their indirect utility

$$s_{i,t} = \arg \max_{j \in \{A, N\}} V_{i,j,t}(k),$$

taking sectoral wages, which adjust endogenously with aggregate labor supply in equilibrium, as given.

Sector Allocations of Ag-born and Nonag-born Workers Let $\phi_{A,t}(k)$ denote the fraction of type- k workers who choose agriculture. The optimal sector choices imply

$$\begin{aligned} \phi_{A,t}(A) &\equiv \mathbb{P}_i[s_{i,t} = A \mid k = A] = \frac{1}{1 + \left[\frac{B_{N,t}}{B_{A,t}} \cdot \frac{w_{N,t}}{w_{A,t}} \cdot \frac{(1-\tau)}{\kappa_A} \right]^\gamma}, \\ \phi_{A,t}(N) &\equiv \mathbb{P}_i[s_{i,t} = A \mid k = N] = \frac{1}{1 + \left[\frac{B_{N,t}}{B_{A,t}} \cdot \frac{w_{N,t}}{w_{A,t}} \cdot \kappa_N \right]^\gamma}. \end{aligned} \tag{1}$$

Fewer ag-born and nonag-born workers choose agriculture when the relative wage or nonpecuniary benefit of nonagriculture is higher. Stronger inherited agricultural skills or preferences increase the fraction of ag-born workers choosing agriculture, while stronger inherited nonagricultural skills reduce the fraction of nonag-born workers choosing agriculture. These inherited mechanisms therefore generate differences in sector choice between workers of different parental backgrounds, even when they face the same wages and common nonpecuniary benefits. Expressions analogous to (1) hold for the fractions of ag-born and nonag-born workers in nonagriculture, which also satisfy $\phi_{N,t}(k) = 1 - \phi_{A,t}(k)$.

Effective Labor Supplied by Ag-born and Nonag-born Workers Let $h_{j,t}(k)$ denote the average effective labor supplied by type- k workers who choose sector j . The Fréchet assumption implies

$$h_{j,t}(k) = \bar{\gamma} \cdot \kappa_j^{\mathbb{1}(k=j)} \cdot \phi_{j,t}(k)^{-1/\gamma}, \tag{2}$$

where $\bar{\gamma} \equiv \Gamma(1 - 1/\gamma)$ and $\Gamma(\cdot)$ is the Gamma function. Holding sector choice probabilities fixed, inherited skill increases workers' average effective labor in their parents' sector. However, workers who are less likely to enter a sector are more positively selected, as cap-

tured by $\phi_{j,t}(k)^{-1/\gamma}$. Thus, differences in average effective labor between parental groups reflect both inherited skill and selection, which can work in opposite directions.

Aggregation and Intergenerational Dynamics The allocation of workers across sectors in period $t - 1$ is a state variable for the economy in period t because it determines the composition of ag-born versus nonag-born workers in the new generation. As such, the aggregate allocation of workers across sectors evolves according to the following law of motion:

$$\phi_{A,t} = \phi_{A,t-1} \cdot \phi_{A,t}(A) + (1 - \phi_{A,t-1}) \cdot \phi_{A,t}(N), \quad (3)$$

where $\phi_{A,t}$ denotes the fraction of all workers in agriculture in period t and $\phi_{A,t-1}$ denotes the fraction of all workers in agriculture in period $t - 1$. Aggregate agricultural employment is the weighted average of the agricultural employment shares of ag-born and nonag-born workers, with weights determined by the previous generation's sectoral allocation. Even though workers make static sector choices, current reallocation affects future aggregate employment by changing the composition of subsequent generations. There is an analogous expression for the fraction of workers in nonagriculture, which moreover satisfies: $\phi_{N,t} = 1 - \phi_{A,t}$.

Aggregate effective labor supply in agriculture is given by:

$$H_{A,t} = \phi_{A,t-1} \cdot \phi_{A,t}(A) \cdot h_{A,t}(A) + (1 - \phi_{A,t-1}) \cdot \phi_{A,t}(N) \cdot h_{A,t}(N), \quad (4)$$

where $H_{A,t}$ denotes the total effective labor supply in agriculture in period t , and an analogous expression holds for $H_{N,t}$. Aggregate effective labor supply in agriculture equals the sum of the effective labor supplied by ag-born and nonag-born workers, accounting for both the number of workers in each group and their average effective labor. Consequently, changes in parental composition affect not only the number of workers in each sector but also the effective labor they supply, which feeds back into equilibrium wages.

Finally, the total labor income in the economy is given by:

$$Y_t = w_{A,t} \cdot H_{A,t} + w_{N,t} \cdot H_{N,t}. \quad (5)$$

Aggregate income equals the sum of wage payments across the two sectors. I next introduce sectoral production and nonhomothetic consumer demand, under which sectoral expenditure shares depend on real income and relative prices.

2.2. Characterizing Aggregate Sectoral Labor Supply Elasticities

Before closing the model, I characterize how workers respond to changes in relative wages and common nonpecuniary benefits, holding the composition of parental groups fixed. Define the within-group relative sectoral labor supply elasticity for type- k workers as

$$\mathcal{E}_t(k) \equiv \frac{\partial \log(\phi_{N,t}(k)/\phi_{A,t}(k))}{\partial \log(w_{N,t}/w_{A,t})} = \frac{\partial \log(\phi_{N,t}(k)/\phi_{A,t}(k))}{\partial \log(B_{N,t}/B_{A,t})} = \gamma.$$

Thus, within each parental group, a 1-percent increase in the relative wage of nonagriculture raises the relative allocation of workers to nonagriculture by approximately γ percent. This common elasticity reflects the idiosyncratic skill heterogeneity among workers with the same parental sector. However, aggregate sector choices also reflect differences between ag-born and nonag-born workers arising from inherited skills and preferences. Consequently, the responsiveness of an entire generation need not equal the common within-group elasticity.

Define the aggregate relative sectoral labor supply elasticity as

$$\mathcal{E}_t \equiv \frac{\partial \log(\phi_{N,t}/\phi_{A,t})}{\partial \log(w_{N,t}/w_{A,t})} = \frac{\partial \log(\phi_{N,t}/\phi_{A,t})}{\partial \log(B_{N,t}/B_{A,t})} = \gamma \cdot \left[1 - \frac{\text{Var}(\mathbb{E}[D_{i,t} | k])}{\text{Var}(D_{i,t})} \right],$$

where $D_{i,t} \equiv 1(s_{i,t} = A)$ is an indicator for whether worker i chooses agriculture. The aggregate responsiveness of workers is equal to the product of the common within-group elasticity and an attenuation term based on between-group sector choice variance.

Proposition 1. *Holding parental composition fixed, the aggregate relative sectoral labor supply elasticity is weakly lower than the relative sectoral labor supply elasticity of type- k workers:*

$$0 < \mathcal{E}_t \leq \mathcal{E}_t(k) = \gamma,$$

with equality if and only if parental sector does not explain any of the variance in sector choice.

Proof. See Appendix [B.1.1](#). □

According to Proposition 1, the aggregate elasticity is smaller than the common within-group elasticity whenever ag-born and nonag-born workers sort differently into sectors. In particular, the attenuation term can be fully expressed in terms of observable sector

choice allocations:

$$\frac{\text{Var}(\mathbb{E}[D_{i,t} | k])}{\text{Var}(D_{i,t})} = \frac{\phi_{A,t-1} \cdot (1 - \phi_{A,t-1}) \cdot [\phi_{A,t}(A) - \phi_{A,t}(N)]^2}{\phi_{A,t} \cdot (1 - \phi_{A,t})}.$$

Conveniently, it is not necessary to know the underlying parameters generating between-group differences in sector choice to compute this attenuation. For a stationary economy (i.e., $\phi_{A,t} = \phi_{A,t-1}$), the attenuation term is simply the squared difference between ag-born and nonag-born workers' agricultural employment shares, $[\phi_{A,t}(A) - \phi_{A,t}(N)]^2$. Hence, any intergenerational persistence in sector choice reduces the aggregate elasticity even when ag-born and nonag-born workers have the same within-group elasticity.

This result has broad implications for the use of Roy–Fréchet models of labor allocation in quantitative macroeconomics and international trade. In models without systematic differences across worker groups, the Fréchet shape parameter γ characterizes both group-specific and aggregate wage responsiveness. Proposition 1 shows that this equivalence breaks down when groups differ systematically in their sector choices, even if they share the same underlying skill distribution. Consequently, interpreting γ as the aggregate labor supply elasticity can overstate how strongly an economy reallocates workers in response to changes in relative wages.

After closing the model by specifying sectoral production and consumer demand below, I characterize how inherited skills and inherited preferences affect structural transformation. I show that this attenuation of the aggregate labor supply elasticity plays a key role in determining how new generations respond to the exogenous changes in fundamentals that drive reallocation.

2.3. Production, Demand, and Equilibrium

I now close the model by introducing sectoral production and consumer demand, and defining the competitive equilibrium.

Production and Labor Demand Each sector has a representative firm that produces output using effective labor as its only input:

$$Q_{j,t} = Z_{j,t} H_{j,t}, \quad j \in \{A, N\}, \quad (6)$$

where $Q_{j,t}$ denotes sectoral output, $H_{j,t}$ is the total effective labor supplied to the sector, and $Z_{j,t} > 0$ denotes its production technology. Firms take the price of their output, $p_{j,t}$, and the wage per efficiency unit of labor, $w_{j,t}$, as given. With linear production, positive output in competitive equilibrium requires

$$w_{j,t} = p_{j,t}Z_{j,t}, \quad j \in \{A, N\}. \quad (7)$$

Thus, wages depend on both sectoral technologies and goods prices, with the latter determined endogenously through consumer demand and goods-market clearing.

Consumer Demand I represent aggregate consumer demand using the nonhomothetic CES expenditure system of [Comin, Lashkari and Mestieri \(2021\)](#), evaluated at aggregate labor income. This specification abstracts from the effects of household income heterogeneity on sectoral demand.

$$\sum_{j \in \{A, N\}} \Omega_j^{1/\sigma} \left(\frac{X_{j,t}}{Q_t^{\vartheta_j}} \right)^{\frac{\sigma-1}{\sigma}} = 1, \quad (8)$$

where $X_{j,t}$ is consumption of sector j goods, Q_t is aggregate consumption, $\Omega_j > 0$ is a sectoral demand weight, $\sigma \in (0, 1)$ governs substitutability between goods, and $\vartheta_N \geq \vartheta_A = 1$ governs differences in their income elasticities. Because $\sigma < 1$, agricultural and nonagricultural goods are complements, so an increase in a good's relative price raises its expenditure share, holding aggregate consumption fixed. Meanwhile, $\vartheta_N > \vartheta_A$ implies that rising aggregate consumption shifts expenditure toward nonagriculture, holding relative prices fixed. When $\vartheta_A = \vartheta_N = 1$, the aggregator reduces to the standard homothetic CES specification, in which changes in aggregate income do not shift relative demand across sectors, holding relative prices fixed.

Define the sectoral expenditure share as $\omega_{j,t} \equiv p_{j,t}X_{j,t}/Y_t$ and the expenditure per unit of aggregate consumption as $P_t \equiv Y_t/Q_t$. Expenditure minimization subject to (8) implies

$$\frac{\omega_{A,t}}{\omega_{N,t}} = \frac{\Omega_A}{\Omega_N} \cdot \left(\frac{p_{N,t}}{p_{A,t}} \right)^{\sigma-1} \cdot Q_t^{(\vartheta_A - \vartheta_N)(1-\sigma)}. \quad (9)$$

This expression summarizes the relative price and income effects on sectoral expenditure shares: a higher relative price of agricultural goods increases agriculture's expenditure share, while higher aggregate consumption shifts expenditure toward nonagriculture.

Competitive Equilibrium Normalize the agricultural goods price to $p_{A,t} = 1$ and define the relative price of nonagricultural goods as $p_t \equiv p_{N,t}/p_{A,t}$. Given an initial agricultural employment share $\phi_{A,0}$, the model parameters, and exogenous paths of sectoral technologies and nonpecuniary benefits, a competitive equilibrium consists of sequences of worker allocations, effective labor supplies, production, consumption, and prices satisfying the following conditions in every period:

1. Workers optimally choose sectors, generating the group-specific employment shares in (1) and average effective labor supplies in (2).
2. Aggregate employment shares and effective labor supplies satisfy (3) and (4), respectively, with analogous expressions for nonagriculture.
3. Competitive firms produce according to (6) and pay wages according to (7). Aggregate labor income satisfies (5).
4. Aggregate consumer demand satisfies the relative expenditure-share relationship in (9), subject to the budget constraint

$$p_{A,t}X_{A,t} + p_{N,t}X_{N,t} = Y_t.$$

Aggregate consumption is determined by (8), with expenditure per unit of consumption given by $P_t = Y_t/Q_t$.

5. Sectoral goods markets clear:

$$X_{j,t} = Q_{j,t}, \quad j \in \{A, N\}. \quad (10)$$

2.4. Implications for Structural Transformation

I now characterize how inherited skills and preferences affect the economy's response to exogenous changes in economic fundamentals. I focus on a permanent 1-percent improvement in agricultural technology, $Z_{A,t}$, holding all other fundamentals fixed. I first examine the *immediate* response of the generation entering the labor market when the shock occurs, and then the *dynamic* effects transmitted to subsequent generations.

For this analysis, I compare three stylized economies. The first ("no-IGP") has no intergenerational persistence ($\kappa_A = \kappa_N = 1$ and $\tau = 0$). The second (" κ -IGP") features inherited skills but no inherited preferences ($\kappa_A, \kappa_N > 1$ and $\tau = 0$). The third (" τ -IGP") features inherited preferences but no inherited skills ($\kappa_A = \kappa_N = 1$ and $\tau > 0$). To obtain

sharp analytical results, I impose the following simplifying assumptions:

Assumption 1. *The three stylized economies satisfy:*

1. *Each economy begins in a stationary equilibrium with the same aggregate agricultural employment share, $\bar{\phi}_A$.*
2. *The κ -IGP and τ -IGP economies have the same positive gap between ag-born and nonag-born workers' agricultural employment shares.*
3. *The κ -IGP economy has symmetric inherited skills: $\kappa_A = \kappa_N > 1$.*
4. *Aggregate consumer demand is homothetic: $\vartheta_A = \vartheta_N = 1$.*

The first two conditions ensure that the stylized economies are comparable. All three begin with the same aggregate worker allocation and experience the same technological improvement. Moreover, the common sector-choice gap, together with stationarity, implies that the κ -IGP and τ -IGP economies have identical worker allocations within each parental group and therefore the same aggregate labor supply elasticity, as established in Proposition 1. Thus, differences in their immediate responses to technological change reflect differences in general equilibrium wage feedback rather than workers' underlying responsiveness to wages.

The remaining conditions simplify the general equilibrium analysis. Symmetric inherited skills eliminate differences in the strength of skill transmission across sectors, while homothetic demand eliminates income-driven shifts in relative sectoral demand. Relative prices still respond to changes in effective labor supplies, allowing me to isolate how inherited skills and preferences generate different wage adjustments. The quantitative analysis later allows inherited skills to differ across sectors and restores nonhomothetic consumer demand. This comparison allows me to distinguish how the source of intergenerational persistence affects both the immediate response to technological change and the subsequent transmission of worker reallocation across generations.

Immediate Effects An improvement in agricultural technology increases the relative abundance of agricultural goods. Because sectoral goods are complements ($\sigma < 1$), the relative price of nonagricultural goods rises sufficiently to increase the relative wage of nonagriculture, holding effective labor supplies fixed. This induces workers in the newest generation to leave agriculture. However, Proposition 1 implies that, for a given increase in the relative wage, worker reallocation is smaller in the two economies with intergener-

ational persistence. Moreover, because the two IGP economies have the same aggregate labor supply elasticity, they exhibit the same initial responsiveness to relative wages.

The full general equilibrium response also depends on how worker reallocation feeds back into relative wages. As workers leave agriculture, relative effective labor supply shifts toward nonagriculture, reducing its relative price and partially offsetting the initial increase in its relative wage. Importantly, the magnitude of this feedback depends on the source of intergenerational persistence. Although the two IGP economies have identical initial worker allocations, they differ in the effective labor supplied by workers in each sector. With inherited preferences, a given reallocation of workers produces a larger increase in relative nonagricultural effective labor supply than with inherited skills. Consequently, the relative wage increases less in the τ -IGP economy, inducing less reallocation out of agriculture.

Proposition 2. *Under Assumption 1, an improvement in agricultural technology induces workers to leave agriculture in all three economies, but the magnitude of the immediate response satisfies*

$$\left. \frac{d\phi_{A,t}}{d \log Z_{A,t}} \right|_{no-IGP} < \left. \frac{d\phi_{A,t}}{d \log Z_{A,t}} \right|_{\kappa-IGP} < \left. \frac{d\phi_{A,t}}{d \log Z_{A,t}} \right|_{\tau-IGP} < 0.$$

Thus, inherited preferences dampen the immediate reallocation out of agriculture more strongly than inherited skills.

Proof. See Appendix B.1.2. □

Thus, even when inherited skills and preferences generate the same aggregate labor supply elasticity, they can have different immediate effects on structural transformation because of their different general equilibrium wage feedbacks. In particular, inherited preferences dampen the immediate reallocation out of agriculture more strongly than inherited skills.

Dynamic Effects Worker reallocation in the current generation also affects the sector choices of future generations by changing the composition of ag-born and nonag-born workers. To isolate this intergenerational transmission, I examine how the agricultural employment share in period t affects the next generation's allocation, holding the path of economic fundamentals fixed.

There are two channels through which this transmission operates. First, when workers leave agriculture in period t , fewer workers in period $t + 1$ are ag-born. Because ag-

born workers are more likely to work in agriculture, this compositional change directly reduces agricultural employment in the next generation. Holding next-generation wages fixed, equation (3) implies

$$\left. \frac{\partial \phi_{A,t+1}}{\partial \phi_{A,t}} \right|_{w_{N,t+1}/w_{A,t+1}} = \phi_{A,t+1}(A) - \phi_{A,t+1}(N) > 0. \quad (11)$$

Thus, the direct dynamic effect propagates reallocation out of agriculture across generations. Moreover, this effect is identical in the κ -IGP and τ -IGP economies at their matched initial allocations.

Second, changes in parental composition also affect the effective labor supplied to each sector, inducing relative wage adjustments. As the fraction of ag-born workers declines, relative effective labor supply shifts toward nonagriculture, reducing its relative wage and opposing the direct dynamic effect. With inherited preferences, this wage adjustment is insufficient to reverse the direct effect, so reallocation out of agriculture continues into the next generation. But with inherited skills, fewer ag-born workers also means fewer workers inheriting agricultural skills and more inheriting nonagricultural skills. This generates a larger shift in relative effective labor supply and a stronger wage adjustment, which can reverse the direct effect and induce workers in the next generation to return to agriculture.

Proposition 3. *Under Assumption 1, the equilibrium response of next-generation agricultural employment to the current generation's allocation satisfies*

$$\left. \frac{d\phi_{A,t+1}}{d\phi_{A,t}} \right|_{no-IGP} = 0, \quad \left. \frac{d\phi_{A,t+1}}{d\phi_{A,t}} \right|_{\tau-IGP} > 0.$$

In the κ -IGP economy, the response can be positive or negative depending on whether the direct effect of changing parental composition or the induced relative wage adjustment dominates.

Proof. See Appendix B.1.3. □

Thus, inherited preferences propagate reallocation in the same direction across generations, whereas inherited skills can reverse its direction.

Cumulative Effects Propositions 2 and 3 establish how intergenerational persistence affects the immediate response to technological change and its transmission to subsequent

generations. However, these results do not establish whether intergenerational persistence ultimately accelerates or slows structural transformation. For sufficiently weak intergenerational persistence, I can characterize the cumulative effects analytically.

Proposition 4. *Under Assumption 1, for a sufficiently small permanent improvement in agricultural technology, sufficiently weak inherited preferences increase reallocation out of agriculture relative to an economy without intergenerational persistence, whereas sufficiently weak inherited skills reduce it. These results hold in every generation after the immediate response and in the long run.*

Proof. See Appendix B.1.4. □

When intergenerational persistence is weak, its immediate dampening of reallocation is second order in the gap between ag-born and nonag-born workers' sector choices, whereas its dynamic effects are first order. Consequently, inherited preferences can accelerate structural transformation even though they initially slow worker reallocation. However, this result need not hold when intergenerational persistence is stronger.

To examine how these results extend to stronger intergenerational persistence, Figure 3 compares the responses to a permanent improvement in agricultural technology across successive generations. I vary the strength of inherited skills and preferences, holding the initial aggregate agricultural employment share fixed across economies. Each response is expressed relative to the no-IGP economy, so positive values indicate greater reallocation out of agriculture.

Figure 3 confirms that both inherited mechanisms dampen immediate reallocation, with inherited preferences generating the larger slowdown for a given degree of persistence. Across subsequent generations, however, their effects diverge. With inherited skills, the dynamic effects reinforce the initial slowdown for the two smaller degrees of persistence, but partially offset it for the largest. Nevertheless, reallocation remains below the no-IGP benchmark in all three cases shown. With inherited preferences, the dynamic effects offset the initial slowdown for all three degrees of persistence. For the smallest degree of persistence, these effects are sufficiently large that the economy eventually re-allocates more workers out of agriculture than the no-IGP economy. For stronger persistence, the dynamic effects are insufficient to overcome the initial slowdown. Appendix Figures 11–14 repeat the exercise under alternative stationary allocations, nonhomothetic demand, Fréchet shape parameters, and elasticities of substitution across goods.

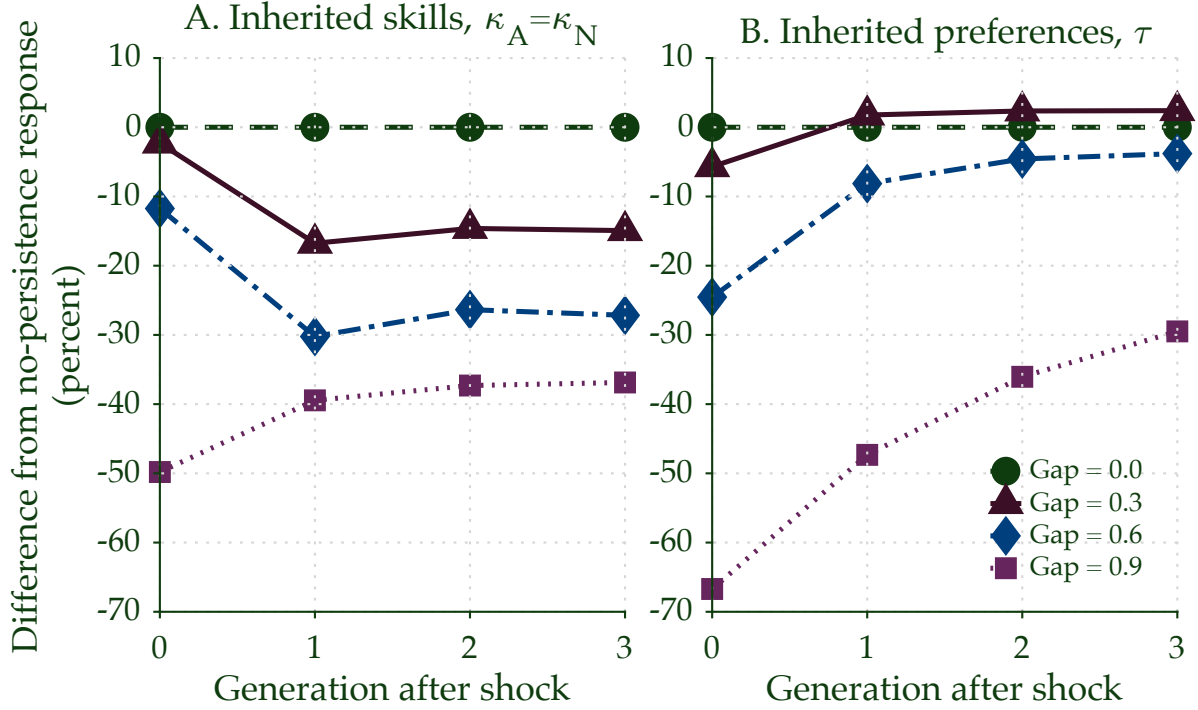


Figure 3: Numerical Responses Relative to No Intergenerational Persistence

Note: The figure reports responses to a permanent 0.01-log-unit increase in agricultural technology, Z_A . Responses are measured relative to the no-IGP benchmark as $100 \times (\text{IGP response}/\text{no-IGP response} - 1)$; positive values indicate faster reallocation, and generation zero is the first exposed to the shock. For each parameterization, fundamentals are separately re-anchored so that the unshocked economy remains at the common stationary agricultural employment share $\bar{\phi}_A = 0.6$. The legend reports the resulting parent-sector employment gap, $\phi_A(A) - \phi_A(N)$. Panel A generates the positive gaps using symmetric inherited skills, $\kappa_A = \kappa_N \in \{1.373, 2.019, 4.403\}$ and $\tau = 0$; Panel B uses inherited preferences, $\tau \in \{0.469, 0.755, 0.948\}$ and $\kappa_A = \kappa_N = 1$. The remaining parameters are $\gamma = 2$, $\sigma = 0.3$, $\vartheta_A = \vartheta_N = 1$, and $\Omega_A = \Omega_N = 1$. This is an illustrative numerical exercise rather than a quantitative calibration to a particular economy.

Thus, inherited preferences can either accelerate or slow structural transformation, depending on the strength of intergenerational persistence. Which mechanism dominates, and by how much, in the historical U.S. economy is a quantitative question that I address in the subsequent analysis.

3. Identification

I now establish how the model's labor supply parameters and exogenous drivers of structural transformation can be identified from workers' earnings, sector choices, and aggregate outcomes. I first characterize the information needed to distinguish inherited skills from inherited preferences. Then, taking these parameters and the consumer demand system as given, I show how the model identifies the exogenous fundamentals in each

period. The estimates and quantitative implementation are presented in the subsequent section.

3.1. Labor Supply Parameters

The labor supply block contains four parameters: the Fréchet shape parameter $\gamma > 1$, inherited skills $\kappa_A \geq 1$ and $\kappa_N \geq 1$, and inherited preferences $\tau \in [0, 1)$. I identify these parameters using variation in workers' earnings and sector choices conditional on their parental sector. The key distinction is that inherited skills affect both earnings and sector choice, whereas inherited preferences affect sector choice without directly affecting earnings. Because earnings also reflect gains from self-selection, identifying inherited skills first requires identifying the Fréchet shape parameter γ .

Fréchet Shape Parameter The Fréchet assumption identifies the skill dispersion parameter from the variance of log earnings conditional on the worker's destination and parental sectors:

$$\gamma = \frac{\pi}{\sqrt{6 \text{Var} [\log y_{i,j,t}(k) \mid s_{i,t} = j, \text{ type } k]}}. \quad (\text{ID-1})$$

Under independent Fréchet skill draws, maximum indirect utility is also Fréchet distributed and independent of which sector provides that maximum. Conditional on destination and parental sector, log earnings differ from log maximum indirect utility only by a constant reflecting common nonpecuniary benefits and inherited preferences. Consequently, the variance of log earnings within each group depends only on γ . Appendix C.1.1 provides the full derivation.

Inherited Skills Given γ , differences in mean earnings across parental groups within a sector identify inherited skills after accounting for self-selection. Let $y_{j,t}(k)$ denote average earnings among type- k workers employed in sector j . Because both parental groups face the same wage per efficiency unit of labor within a sector, equation (2) identifies inherited agricultural skills as

$$\kappa_A = \frac{y_{A,t}(A)}{y_{A,t}(N)} \cdot \left(\frac{\phi_{A,t}(A)}{\phi_{A,t}(N)} \right)^{1/\gamma}. \quad (\text{ID-2})$$

The average earnings gap in agriculture reflects both inherited agricultural skills and the different gains from self-selection of ag-born and nonag-born workers into agriculture.

Likewise, inherited nonagricultural skills are identified as

$$\kappa_N = \frac{y_{N,t}(N)}{y_{N,t}(A)} \cdot \left(\frac{\phi_{N,t}(N)}{\phi_{N,t}(A)} \right)^{1/\gamma}. \quad (\text{ID-3})$$

Together, the two earnings ratios identify κ_A and κ_N once the relative gains from self-selection have been removed using observed sector choices and the identified γ .

Inherited Preferences Finally, inherited preferences are identified from the remaining differences in sector choice between ag-born and nonag-born workers. Define the odds of agricultural employment for ag-born workers relative to nonag-born workers as

$$\mathcal{O} \equiv \frac{\phi_{A,t}(A)/\phi_{N,t}(A)}{\phi_{A,t}(N)/\phi_{N,t}(N)}.$$

Equation (1) identifies inherited preferences as

$$\tau = 1 - \frac{\kappa_A \kappa_N}{\mathcal{O}^{1/\gamma}}. \quad (\text{ID-4})$$

The relative wage and common nonpecuniary benefits cancel from the odds ratio because both parental groups face the same sectoral incentives apart from their inherited skills and preferences. Consequently, observed sector choices identify τ conditional on γ , κ_A , and κ_N .

Identification Assumptions The identification of the labor supply parameters relies on two assumptions embedded in the model. First, workers draw independent sector-specific skills from a common Fréchet distribution. This restriction delivers the closed-form relationships between workers' sector choices, earnings, and the four labor supply parameters. In the quantitative application, I assess the sensitivity of the parameter estimates to alternative skill distributions that allow for sector-specific skill dispersion and correlation across sectoral skills.

Second, ag-born and nonag-born workers must face the same wage per efficiency unit of labor within each sector. Otherwise, differences in earnings between parental groups could reflect differences in wages rather than inherited skills. Such wage differences might arise because workers from different parental backgrounds live in different local labor markets, or because employers condition wage offers on family connections or background. In the quantitative application, I assess the sensitivity of the estimates to local

labor-market differences and restrict attention to workers employed outside their childhood commuting zones. However, these exercises cannot rule out wage differences by parental background within sectors, which remain a maintained identifying assumption.

3.2. Exogenous Drivers of Structural Transformation

I next establish how aggregate economic outcomes identify the exogenous drivers of structural transformation. These are the sectoral technologies, $Z_{A,t}$ and $Z_{N,t}$, and the common nonpecuniary benefits, $B_{A,t}$ and $B_{N,t}$. Only the relative benefit $B_{N,t}/B_{A,t}$ is identified because a common proportional change in both benefits does not affect sector choices. Conditional on the model parameters and the previous generation's agricultural employment share, I identify these three fundamentals using the aggregate agricultural employment share, $\phi_{A,t}$, relative goods prices, p_t , and real consumption, Q_t .

Proposition 5 (Identification of Fundamentals). *Fix the labor-supply and consumer-demand parameters and normalize $p_{A,t} = 1$. Given $\phi_{A,t-1} \in (0, 1)$, the observed outcomes $\phi_{A,t} \in (0, 1)$, $p_t > 0$, and $Q_t > 0$ uniquely identify $Z_{A,t}$, $Z_{N,t}$, and $B_{N,t}/B_{A,t}$, provided the outcomes are consistent with the model.*

Proof. See Appendix C.1.2. □

First, given the labor supply parameters, the model implies an intergenerational sector-choice odds ratio of $\mathcal{O} = (\kappa_A \kappa_N / (1 - \tau))^\gamma$. Together with the aggregate employment equation (3), this relationship uniquely determines $\phi_{A,t}(A)$ and $\phi_{A,t}(N)$ from the observed agricultural employment share and the previous generation's allocation. Equations (2) and (4) then determine the effective labor supplied to each sector.

Second, relative goods demand and market clearing identify relative sectoral technology:

$$\frac{Z_{N,t}}{Z_{A,t}} = \frac{H_{A,t}}{H_{N,t}} \cdot \frac{\Omega_N}{\Omega_A} \cdot p_t^{-\sigma} \cdot Q_t^{(\vartheta_N - \vartheta_A)(1-\sigma)}. \quad (\text{ID-5})$$

Thus, relative technology is identified from observed relative prices and real consumption, together with the effective labor supplies implied by workers' sector choices.

Third, the nonhomothetic CES demand system identifies the level of agricultural technology:

$$Z_{A,t} = \frac{\Omega_A Q_t^{\vartheta_A}}{H_{A,t}} \cdot \left[\Omega_A + \Omega_N \left(p_t Q_t^{\vartheta_N - \vartheta_A} \right)^{1-\sigma} \right]^{\frac{\sigma}{1-\sigma}}. \quad (\text{ID-6})$$

The level of nonagricultural technology follows from the previously identified relative technology. Hence, observed real consumption determines the levels of both technologies, conditional on their relative magnitude.

Finally, the sector choices of nonag-born workers and the competitive wage condition identify the relative nonpecuniary benefit:

$$\frac{B_{N,t}}{B_{A,t}} = \frac{1}{\kappa_N} \cdot \left(\frac{\phi_{N,t}(N)}{\phi_{A,t}(N)} \right)^{1/\gamma} \cdot \frac{Z_{A,t}}{p_t Z_{N,t}}. \quad (\text{ID-7})$$

Thus, the relative benefit is identified after accounting for the relative wage implied by sectoral technologies and goods prices.

Together, these relationships uniquely identify the three exogenous fundamentals from the observed aggregate outcomes, conditional on the model parameters and the inherited worker composition. The full derivation and proof of uniqueness are provided in Appendix [C.1.2](#).

Identification is period-by-period but recursive because $\phi_{A,t}$ determines the composition of ag-born and nonag-born workers in period $t + 1$. The consumer demand parameters are treated as given here and are calibrated in the subsequent quantitative application.

4. Quantitative Application: U.S. Industrialization

Here I quantify how intergenerational persistence shaped U.S. industrialization between 1880 and 1940. I first estimate the labor supply parameters using linked historical census records and then calibrate consumer demand using aggregate historical data. Next, I infer the sectoral technologies and common nonpecuniary benefits that reproduce the observed transition. Finally, I simulate counterfactual economies to evaluate how inherited skills and preferences affected the reallocation of workers out of agriculture.

4.1. Estimation of Labor Supply Parameters

I now estimate the four labor supply parameters using the identifying relationships established in Section [3.1](#). The strategy combines workers' sector choices with earnings distributions within sectors to distinguish inherited skills from inherited preferences. Because 1940 is the first U.S. census to report individual wage and salary earnings, I estimate these

parameters using the linked 1940 census and hold them fixed throughout the subsequent historical analysis.

I focus on U.S.-born employed men aged 20–29 whose fathers’ sectors of employment are observed in an earlier census. I use three samples for the corresponding moments. Sector-choice probabilities use the full linked sample with observed worker and parental sectors, and the mean hourly-earnings moments used to estimate inherited skills use workers with positive wage and salary income, positive weeks worked, and positive usual weekly hours. The residual earnings variance used to estimate γ further requires at least 40 weeks worked and at least 35 usual weekly hours. This restriction excludes workers without reported wage and salary income including self-employed farmers. This is a substantive limitation of the data I discuss after presenting the results.⁸

The model abstracts from differences in age, race, and local labor-market conditions that may also influence workers’ earnings. If these differences reflect variation in wages or other determinants of earnings beyond the sector-specific skills in the model, they may affect the moments used to identify the labor supply parameters. My baseline therefore adjusts the earnings and sector-choice moments for age and race fixed effects. I also report a location specification that additionally includes adulthood commuting-zone fixed effects. However, adulthood location may itself reflect workers’ inherited skills and preferences through their employment and migration decisions, so conditioning on location need not remove only extraneous variation. I therefore use the age-and-race-adjusted estimates as my baseline and use the location estimates to assess sensitivity to local labor-market heterogeneity.

Estimates of γ I first estimate the Fréchet shape parameter γ , which governs the distribution of workers’ skills. As established in equation (ID-1), the variance of log earnings within a given worker-sector-by-parental-sector group depends only on γ in the model. I therefore remove the means of these groups together with age and race fixed effects from log hourly earnings and use the residual variance to recover γ . The baseline estimate is $\hat{\gamma} = 2.195$.

Although the model abstracts from differences in age and local labor market conditions, these factors may contribute to earnings dispersion beyond the idiosyncratic skills in the

⁸Another limitation of the data is that income is topcoded at \$5,000 in the 1940 census, affecting about 0.1 percent of workers in the estimation sample. This may lead to an underestimation of the true earnings of high-income workers. I address this by rescaling topcoded incomes to match the historical top-income share reported by [Atkinson, Piketty and Saez \(2011\)](#) and show that this adjustment has almost no effect on the estimates. These estimates are reported in Appendix [A.2.5](#).

model. In particular, if the wages per efficiency unit differ along these dimensions, the residual variance of log earnings may overstate the true dispersion of skills and lead to an underestimate of γ . I therefore report an estimate that additionally controls for adulthood commuting-zone fixed effects.

Table 1: Estimates of the Fréchet Shape Parameter

	Baseline	Location
$\hat{\gamma}$	2.195 (0.033)	2.319 (0.033)
Observations	2,077,253	2,077,253
Quantile RMSE (1st–99th percentiles)	0.322	0.303

Note: Both columns infer γ from the residual variance of log hourly earnings after including worker-sector-by-parental-sector, age, and race fixed effects; column 2 additionally includes adult commuting-zone fixed effects. Commuting-zone cluster-bootstrap standard errors are reported in parentheses and use 499 resamples of adult commuting zones. Both columns use 2,077,253 observations with positive earnings, at least 40 weeks worked, and at least 35 weekly hours; no log-earnings restriction is imposed. Quantile RMSE measures fit across the 1st–99th residual percentiles in log points; lower values indicate better fit.

Having recovered γ , I can account for the different gains from self-selection of ag-born and nonag-born workers when interpreting their mean earnings within the same sector.

Estimates of Inherited Skills and Preferences The average earnings of ag-born and nonag-born workers within a sector reflect both inherited skills and the selection of workers into that sector. As equations (ID-2) and (ID-3) show, the sector-choice probabilities of each parental group, together with $\hat{\gamma}$, allow me to adjust the observed earnings ratios for these differences in selection. The remaining differences in sector choice then identify inherited preferences according to equation (ID-4). I use mean earnings from the broader positive-hourly-earnings sample and sector-choice probabilities from the full linked sample to implement these relationships. Table 2 reports the results.

Figure 4 connects these estimates to the reduced-form earnings comparison in Figure 2. Because earnings differences are decomposed additively in logs, the multiplicative parameter estimates enter the figure as $\log(\hat{\kappa}_A) = 0.404$ in agriculture and $-\log(\hat{\kappa}_N) = -0.552$ in nonagriculture. In agriculture, inherited skill contributes 0.404 log point to ag-born workers’ relative earnings, but their weaker positive selection contributes -1.030 log points; selection therefore more than offsets their inherited agricultural skill advantage and produces a net gap of -0.627 . In nonagriculture, inherited skill contributes -0.552 log point and selection contributes 0.317 log point, yielding a net gap of -0.235 .

Table 2: Inherited Skills and Preferences

	Baseline	Location
Inherited Skills, $\hat{\kappa}_A$	1.497 (0.033)	1.306 (0.020)
Inherited Skills, $\hat{\kappa}_N$	1.736 (0.027)	1.422 (0.022)
Inherited Preferences, $\hat{\tau}$	0.324 (0.020)	0.284 (0.013)

Note: The table reports inherited skills, $\hat{\kappa}_A$ and $\hat{\kappa}_N$, and inherited preferences, $\hat{\tau}$, estimated from hourly earnings and sector choices in the linked 1940 census. Commuting-zone cluster-bootstrap standard errors are reported in parentheses and use 499 resamples of adult commuting zones; every resample jointly re-estimates γ , the earnings moments, and the sector-choice moments. Columns 1 and 2 use the baseline and location estimates of γ from Table 1. Both columns adjust the underlying earnings and sector-choice moments for age and race fixed effects; column 2 additionally includes adult commuting-zone fixed effects. Earnings moments entering κ_j use the broader positive-hourly-earnings sample described above; all sector-choice moments use the full sample of workers with valid worker and parental sectors.

In the data, the decomposed gaps need not equal the reduced-form coefficients because the former are log ratios of arithmetic mean earnings and the latter are differences in mean log earnings, even on the same sample. For corresponding population comparisons, the common-shape Fréchet model implies equality between these two objects; I retain both empirical markers and do not impose their equality in the sample. The decomposed and reduced-form gaps are nearly identical in agriculture; in nonagriculture, the decomposed gap is 0.053 log point less negative than the reduced-form coefficient.

The agricultural earnings gap illustrates why accounting for selection is essential. Among agricultural workers, the age-and-race-adjusted hourly earnings means are approximately \$0.19 for ag-born workers and \$0.36 for nonag-born workers. However, the corresponding agricultural employment probabilities are 52.9 percent for ag-born workers and only 5.5 percent for nonag-born workers. The relatively few nonag-born workers who enter agriculture are therefore much more positively selected on their agricultural skills. At the estimated γ , the model implies gains from self-selection of approximately 34 percent for ag-born agricultural workers and 275 percent for nonag-born agricultural workers. After adjusting for this difference, I estimate $\hat{\kappa}_A = 1.497$, implying that ag-born workers can supply approximately 50 percent more effective labor to agriculture than otherwise identical nonag-born workers. The corresponding adjustment in nonagriculture yields $\hat{\kappa}_N = 1.736$, implying an inherited nonagricultural skill advantage of approximately 74 percent for nonag-born workers.

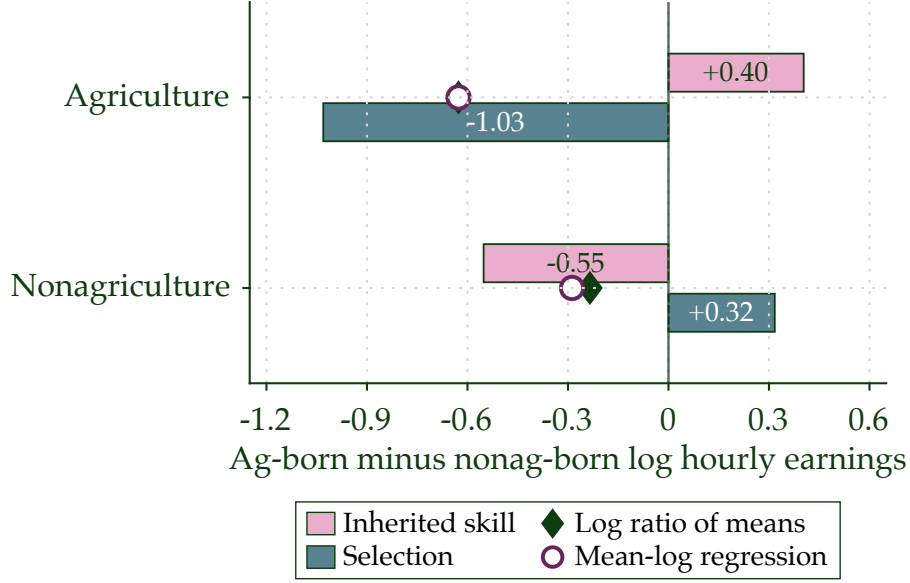


Figure 4: Inherited Skills, Selection, and Within-Sector Earnings Gaps

Note: All quantities use the sign convention ag-born minus nonag-born log hourly earnings in the indicated destination sector. The inherited-skill component is $\log(\hat{\kappa}_A)$ in agriculture and $-\log(\hat{\kappa}_N)$ in nonagriculture. The selection component is $-\hat{\gamma}^{-1} \log[\hat{\phi}_j(A)/\hat{\phi}_j(N)]$, where $\hat{\phi}_j(p)$ is the probability that parental group p chooses sector j . Each colored bar begins at zero and reports the signed contribution of the indicated component; the solid diamond marks their sum, which equals the log ratio of mean hourly earnings used by the baseline structural estimator up to numerical precision. The hollow circle reproduces the baseline age-and-race-adjusted coefficient from Figure 2, a difference in mean log hourly earnings estimated on the same positive-hourly-earnings sample. Thus, the diamond and circle use the same earnings sample but differ because the former is a log ratio of arithmetic means and the latter is a difference in mean logs; sector-choice probabilities entering the decomposition use the full linked sample. The location decomposition is omitted because its adulthood-commuting-zone adjustment does not match the fully interacted childhood-by-adulthood commuting-zone specification in Figure 2.

Inherited skills explain a substantial portion of the observed persistence in sector choice, but not all of it. In the 1940 linked sample, the age-and-race-adjusted odds of working in agriculture are approximately 19.3 times higher for ag-born workers than for nonag-born workers. Given $\hat{\gamma}$, the estimated inherited skills alone would imply an odds ratio of approximately 8.1, so the remaining persistence is attributed to inherited preferences. I estimate $\hat{\tau} = 0.324$, implying that ag-born workers value nonagricultural employment approximately 32 percent less, holding their potential earnings and common nonpecuniary benefits fixed. In the additive decomposition of log-odds persistence, inherited skills account for 70.9 percent and inherited preferences for the remaining 29.1 percent, as derived in Appendix A.2.1.

Interpreting these estimates requires distinguishing between two forms of selection. The model explicitly accounts for workers' selection into sectors, but the income data do not observe the earnings of all workers within a sector. In particular, the 1940 cen-

sus excludes self-employment income, so I observe wage and salary earnings for only about 46 percent of agricultural workers and 90 percent of nonagricultural workers in the linked sample.⁹ To use the observed earnings moments as estimates of the population moments, I must assume that selection into the earnings sample is independent of latent skills conditional on destination and parental sector. For example, if relatively skilled ag-born workers disproportionately enter self-employed farming, their absence from the earnings sample could lead me to underestimate inherited agricultural skills and, consequently, overestimate the role of inherited preferences. This is an important limitation of the data that the model's correction for sectoral self-selection does not resolve.

A separate concern is that earnings differences between parental groups could reflect differences in the wages they face within a sector rather than inherited skills. Such wage differences may arise from the different local labor markets occupied by ag-born and nonag-born workers or from employers' treatment of workers with different family backgrounds. The location estimates add adulthood commuting-zone fixed effects to the baseline age and race controls and continue to imply substantial inherited skills and preferences. Appendix Table 11 shows that these mechanisms also remain economically meaningful among workers employed outside their childhood commuting zones, although this exercise cannot rule out parental-background-specific wages or selection into migration.

Finally, the adjustment for sectoral self-selection depends on the assumed distribution of workers' skills. Appendix Table 12 reports estimates using alternative joint skill distributions that allow for sector-specific dispersion and dependence across skills. These specifications imply materially different divisions of persistence between inherited skills and preferences, so I carry the alternative estimates through the counterfactual analysis to assess how sensitive the macroeconomic results are to this assumption.

4.2. Consumer Demand Calibration

I set $\sigma = 0.3$, consistent with the estimates in [Comin, Lashkari and Mestieri \(2021\)](#). I normalize $\Omega_N = 1$ and $\vartheta_A = 1$, calibrate Ω_A from the initial agricultural output share, and choose $\vartheta_N > \vartheta_A$ by minimum distance. I observe the agricultural output share, $\omega_{A,t}$, from [Dennis and İřcan \(2009\)](#), the relative price $p_t \equiv p_{N,t}/p_{A,t}$ from [Alvarez-Cuadrado and Poschke \(2011\)](#), and real GDP per capita, Y_t/P_t , from [Maddison \(1995\)](#) for each year $t \in \{1880, 1900, 1920, 1940\}$. I scale both the relative price and real GDP per capita to be

⁹[Carruthers and Wanamaker \(2017\)](#) discuss the related limitation posed by the absence of self-employment earnings in the 1940 census.

equal to one in 1880, so that the 1880 agricultural output share determines the relative demand shifters.

By normalizing $\Omega_N = 1$, I calibrate Ω_A to match the 1880 agricultural output share:

$$\Omega_A = \frac{\omega_{A,1880}}{\omega_{N,1880}}$$

Then, I choose ϑ_N by minimum distance to the observed agricultural output shares:

$$\hat{\vartheta}_N = \arg \min_{\vartheta_N > 1} \sum_{t \in \{1900, 1920, 1940\}} (\omega_{A,t} - \hat{\omega}_{A,t}(\vartheta_N; \sigma = 0.3))^2.$$

The model-implied relative expenditure share used in this calibration is

$$\frac{\hat{\omega}_{A,t}}{1 - \hat{\omega}_{A,t}} = \Omega_A \left(\frac{p_{N,t}}{p_{A,t}} \right)^{\sigma-1} \left(\frac{Y_t}{P_t} \right)^{(1-\vartheta_N)(1-\sigma)}.$$

The minimum-distance estimate of the nonagricultural nonhomotheticity parameter is $\hat{\vartheta}_N = 4.63$. Appendix Figure 15 plots the observed and model-implied agricultural output shares from the baseline calibration. By design, the model exactly matches the observed agricultural output share in 1880, and its largest discrepancy thereafter is 1.5 percentage points in 1920.

4.3. Inferring Drivers of U.S. Structural Transformation

I exploit the model's structure along with observed agricultural employment shares, relative prices, and real GDP per capita to infer the sectoral technologies and relative payoff shifter that exactly replicate the historical evolution of U.S. structural transformation out of agriculture.

The identification result in Proposition 5 establishes that the observed agricultural employment share, relative goods price, and real GDP per capita uniquely determine the period-specific technologies and relative nonpecuniary benefit, conditional on the model parameters. I apply this inversion recursively to the historical data, using the previous census period's agricultural employment share to determine the parental composition of the current generation. Appendix C.1.2 provides the formal derivation and proof, while Appendix D.1 documents the quantitative implementation.

Table 3 summarizes the benchmark parameters and their empirical discipline.

Table 3: Benchmark Model Parameters

Parameter	Interpretation	Value	Method	Empirical discipline
<i>Panel A: Labor Supply</i>				
γ	Fréchet shape parameter	2.195	Estimated	Within-group variance of log hourly earnings, conditional on age and race.
κ_A	Inherited agricultural skills	1.497	Estimated	Agricultural earnings differences by parental sector, adjusted for self-selection.
κ_N	Inherited nonagricultural skills	1.736	Estimated	Nonagricultural earnings differences by parental sector, adjusted for self-selection.
τ	Inherited preferences	0.324	Estimated	Intergenerational sector-choice odds ratio, net of inherited skills.
<i>Panel B: Consumer Demand</i>				
Ω_A	Agricultural demand weight	0.449	Calibrated	Agricultural output share in 1880.
Ω_N	Nonagricultural demand weight	1	Normalized	Relative demand-weight normalization.
σ	Elasticity of substitution	0.300	Externally set	Comin, Lashkari and Mestieri (2021) .
ϑ_A	Agricultural income parameter	1	Normalized	Reference income-exponent normalization.
ϑ_N	Nonagricultural income parameter	4.630	Calibrated	Minimum-distance fit to agricultural output shares in 1900, 1920, and 1940.
<i>Panel C: Initial Condition</i>				
$\phi_{A,0}$	Initial agricultural employment share	0.665	Observed	Agricultural employment share in 1860, determining the composition of workers in 1880.

Note: Labor-supply parameters are estimated using the linked 1940 census, with earnings and sector-choice moments adjusted for age and race. The estimate of γ uses workers with positive hourly earnings, at least 40 weeks worked, and at least 35 usual weekly hours. The inherited-skill estimates use a broader positive-hourly-earnings sample, while sector-choice moments use the full linked sample. Consumer demand parameters are calibrated using historical agricultural output shares, relative prices, and real GDP per capita.

In Appendix Figure 16, I plot the observed agricultural employment share, relative price, and real GDP per capita that are used to identify the sectoral technologies and relative payoff shifter in each year. While the inversion exactly matches the aggregate agricultural employment share, it generally does not match the subgroup employment shares of ag-born and nonag-born workers. I plot observed and model-implied subgroup agricultural employment shares in Appendix Figure 17. This mismatch emerges because the extent of intergenerational persistence changes somewhat over time, but my calibration holds the inherited skills and preferences fixed at their estimated 1940 values. Most notably, the model implies a much higher agricultural employment share for nonag-born workers in 1880 than is observed in the data. Within the current model, matching the subgroup paths would require time-varying inherited-skill or inherited-preference parameters, or an additional mechanism. Without income microdata prior to 1940, estimating such time variation would require maintained assumptions about the evolution of intergenerational persistence that are not supported by data. I therefore interpret the inferred fundamentals as those required to rationalize the aggregate transition conditional on holding the 1940 inherited-skill and inherited-preference parameters fixed, rather than as a decomposition that separately identifies historical changes in persistence.

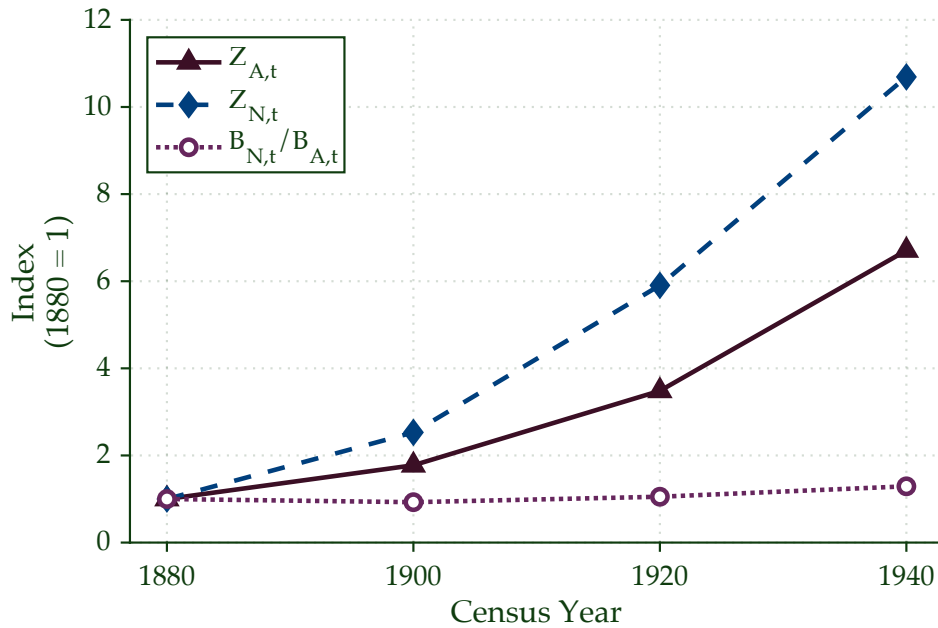


Figure 5: Inferred Drivers of U.S. Structural Transformation, 1880-1940

Note: The figure plots the agricultural and nonagricultural technologies, $Z_{A,t}$ and $Z_{N,t}$, and the relative payoff shifter, $B_{N,t}/B_{A,t}$, inferred from the targeted moments in Appendix Figure 16. Each series is indexed to one in 1880; subsequent values are recovered recursively under the baseline parameters in Table 3.

The inferred sectoral technologies and relative payoff shifter, each indexed to their 1880

values, are plotted in Figure 5. I infer dramatic growth in the nonagricultural and, to a lesser extent, the agricultural technology between 1880 and 1940. In particular, the nonagricultural technology is 10.7 times larger in 1940 than in 1880, while the agricultural technology is about 6.7 times larger. The relative payoff shifter also contributes to the reallocation of workers out of agriculture, but its evolution is much more modest: about 29 percent larger in 1940 than in 1880.

Because these fundamentals are inferred through the model, their measured growth depends on whether the inversion accounts for intergenerational persistence. Figure 6 repeats the inversion after imposing no inherited skills or inherited preferences, while holding γ and the consumer demand parameters fixed. Without IGP, matching the same observed outcomes requires substantially faster relative nonagricultural technology growth: the 1880–1940 increase in $Z_{N,t}/Z_{A,t}$ rises from 46.6 to 77.8 log points. Conversely, the inferred increase in $B_{N,t}/B_{A,t}$ falls from 25.6 to 8.1 log points. Thus an inversion that omits IGP attributes more of the observed worker reallocation to relative technology growth and less to changes in relative sectoral payoffs. For comparison, the nonfarm-to-farm relative TFP series constructed by [Alvarez-Cuadrado and Poschke \(2011\)](#) rises by 55.5 log points over the same period, much closer to the baseline than the no-IGP inversion.

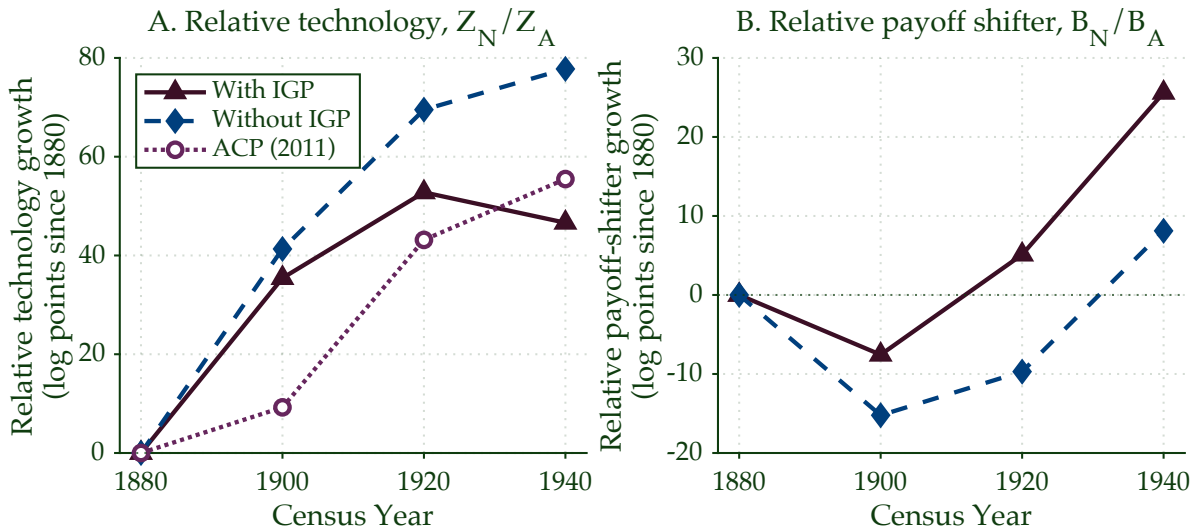


Figure 6: Inferred Relative Drivers With and Without Intergenerational Persistence

Note: Panel A plots the cumulative log change in relative technology, $Z_{N,t}/Z_{A,t}$; Panel B plots the cumulative log change in the relative payoff shifter, $B_{N,t}/B_{A,t}$. Both model series are normalized to zero in 1880. Panel A also plots the U.S. nonfarm-to-farm relative TFP series from the replication data of [Alvarez-Cuadrado and Poschke \(2011\)](#). Because that series is observed in 1879 and 1884 but not 1880, I linearly interpolate its 1880 level; its values in 1900, 1920, and 1940 are observed directly. The baseline inversion uses the estimated inherited skills and preferences. The no-IGP inversion imposes $\kappa_A = \kappa_N = 1$ and $\tau = 0$, while holding γ and all consumer demand parameters fixed. Both inversions match the same agricultural employment share, relative price, and real GDP per capita in each year.

Appendix Figure 18 decomposes this difference across the two sources of persistence. Removing inherited skills alone raises inferred relative nonagricultural technology growth from 46.6 to 76.2 log points, nearly the 77.8 log points inferred without any intergenerational persistence, whereas removing inherited preferences raises it only to 50.0 log points. Thus, the change in the model’s interpretation of U.S. industrialization comes primarily from accounting for inherited skills rather than inherited preferences.

4.4. Counterfactual U.S. Structural Transformation

In order to quantify the role of inherited skills and inherited preferences in shaping U.S. structural transformation, I simulate the model after removing each source of persistence separately and then both together. I consider three counterfactuals. First, I remove inherited skills by setting $\kappa_A = \kappa_N = 1$ while retaining the inherited preferences of ag-born workers by keeping $\tau = 0.324$. Second, I remove inherited preferences by setting $\tau = 0$ while retaining inherited skills at $\kappa_A = 1.497$ and $\kappa_N = 1.736$. Third, I remove both sources of intergenerational persistence by setting $\kappa_A = \kappa_N = 1$ and $\tau = 0$.

For each counterfactual, I re-infer the sectoral technologies and relative payoff shifter that exactly replicate the observed agricultural employment share, relative price, and real GDP per capita in 1880. Then, I simulate the model forward under the corresponding persistence parameters using the inferred growth in sectoral technologies and relative payoff shifter depicted in Figure 5. By construction, the counterfactual simulations exactly match the observed outcomes in 1880, but they generally do not match the observed outcomes thereafter.

Table 4: Cumulative Effects on U.S. Worker Reallocation, 1880–1940

Counterfactual	Cumulative worker reallocation	Cumulative effect (relative to benchmark)	
	Percentage points	Percentage points	Percent
Benchmark	38.3	–	–
No inherited skills	43.6	5.3	13.9
No inherited preferences	39.1	0.8	2.1
No intergenerational persistence	43.2	4.9	12.8

Note: Cumulative worker reallocation is the 1880–1940 decline in the agricultural employment share; cumulative effects are relative to the benchmark, in percentage points and as a percent of benchmark reallocation. Each counterfactual is re-anchored to the 1880 employment share, relative price, and real GDP per capita, then simulated using benchmark growth in the inferred technologies and relative payoff shifter.

Table 4 compares the decline in the agricultural employment share between 1880 and 1940 under each counterfactual to the benchmark/observed decline. Removing inherited skills increases worker reallocation out of agriculture by 5.3 percentage points, or 13.9 percent of benchmark reallocation. Removing inherited preferences increases worker reallocation by 0.8 percentage points, or 2.1 percent of benchmark reallocation. Removing both sources of intergenerational persistence increases worker reallocation by 4.9 percentage points, or 12.8 percent of benchmark reallocation.¹⁰

I next decompose the cumulative effect of each counterfactual into the two channels highlighted by the analytical results: the immediate effect of changing fundamentals on the current generation and the dynamic effect transmitted through subsequent changes in parental composition. These two channels interact in equilibrium; hence, their measured contributions depend on the order in which they are changed. As such, I use a Shapley decomposition, which assigns each channel its average marginal contribution across the possible orderings. I implement this decomposition within each historical interval and sum the resulting contributions over 1880–1940.

Table 5: Immediate and Dynamic Components of Cumulative Effects

Counterfactual	Immediate effect	Dynamic effect	Cumulative effect
	Percentage points		
No inherited skills	2.42	2.91	5.33
No inherited preferences	3.09	−2.27	0.82
No intergenerational persistence	3.49	1.42	4.91

Note: The interval-level Shapley decomposition averages over the two orders in which fundamentals and parental composition change. The immediate effect varies technologies and the relative payoff shifter holding parental composition fixed; the dynamic effect varies parental composition holding those fundamentals fixed. The cumulative effect is the sum of these two contributions over 1880–1940, measured relative to the benchmark, and equals the counterfactual reallocation difference in Table 4.

Table 5 shows that removing inherited skills increases worker reallocation through both channels, with the dynamic effect accounting for 2.91 of the cumulative 5.33 percentage point effect. Removing inherited preferences generates a large immediate increase in worker reallocation that is mostly offset by the dynamic effect of the resulting change in parental composition. When I remove both sources of intergenerational per-

¹⁰For reference, the U.S. industrialization lost to intergenerational persistence is comparable to the Chinese industrialization spurred by modern labor mobility reforms. Brandt, Hsieh and Zhu (2008) estimate that the 1978–2004 decline in China’s agricultural employment share would have been 8 percentage points (21 percent) smaller without the observed reductions in agricultural versus nonagricultural wage gaps that they attribute to mobility reforms.

sistence, the immediate effect increases worker reallocation by 3.49 percentage points, while the dynamic effect contributes 1.42 percentage points. The additional reallocation from removing all intergenerational persistence is 4.91 percentage points in the baseline, 3.08 under the location-adjusted labor-supply parameters, and 5.05 under the alternative CLM consumer-demand calibration. Appendix Table 19 reports those calibration checks. Across the alternative skill-distribution estimates in Appendix Table 21, the corresponding effect ranges from 2.13 percentage points under the bivariate lognormal specification to 6.95 under the Fréchet–Frank specification; in both cases, removing inherited skills has the larger cumulative effect, while the immediate effect of removing inherited preferences is substantially offset dynamically.

5. Conclusion

New generations entering the labor force may be more flexible than incumbent workers, but their sector choices are not independent of their parents' sectors. Using linked historical U.S. census records and a macroeconomic model of structural transformation, I find that removing intergenerational persistence would have increased the decline in agricultural employment between 1880 and 1940 by approximately 4.9 percentage points. Most of this effect comes from inherited skills, which dampen the immediate reallocation out of agriculture and reinforce this slowdown across subsequent generations through changes in effective labor supply and relative wages. Inherited preferences also dampen immediate reallocation, but their dynamic effects largely offset the initial slowdown. Accounting for these inherited mechanisms also changes the sectoral technological progress the model infers from the observed transition.

These findings have implications beyond U.S. industrialization. Intergenerational mobility is often studied for its implications for inequality and economic opportunity (OECD, 2018; Narayan et al., 2018), but inherited connections also shape how an economy responds to economic change. Even though ag-born and nonag-born workers have the same within-group sector-choice elasticity, their different sector choices reduce the responsiveness of the aggregate labor force to relative wages. Models that abstract from these differences may therefore overstate how strongly wage changes translate into worker reallocation. Moreover, distinguishing inherited skills from inherited preferences matters because their effects on reallocation differ both immediately and across generations.

One direction for future work is to apply this framework to contemporary develop-

ing economies, where agricultural occupations are often transmitted across generations and labor reallocation can lag agricultural productivity growth ([Emran and Shilpi, 2011](#); [Krishna and Meenakshi, 2022](#)). Linked data on parents' sectors, workers' earnings, and sector choices could help establish whether inherited skills or preferences contribute to slower structural transformation.

Another direction is to incorporate intergenerational persistence into models of adjustment to shorter-run sectoral shocks, including trade shocks. Recent evidence suggests that the eventual recovery of U.S. labor markets exposed to import competition came disproportionately from workers who were below working age when the shock began ([Autor et al., 2025](#)). Allowing these workers' sector choices to depend on their parents' sectors could reveal whether the arrival of new generations dampens or propagates the effects of such shocks.

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A. Appendix: Empirical Results

A.1. Data Construction

This appendix documents linked-census sample construction and reports additional robustness results for the intergenerational-persistence estimates.

A.1.1. MLP Sample Selection

Appendix Table 6 documents how the MLP linkage procedure changes the analysis sample. Panel A begins with U.S.-born employed men ages 20–29 with a valid current industry and reports the number linked to a childhood census record, the number for whom a father is identified in the childhood household, and the number with a valid paternal industry. The final sample ranges from 49 percent of eligible workers in 1880 to 68 percent in 1940. Panel B compares the full eligible population with the final linked sample in 1940. Despite the reduction in sample size, the two samples are similar along the observed dimensions reported in the table. The linked sample is modestly more agricultural, white, and educated and modestly less urban and Southern, while its sector-specific earnings moments remain close to those in the full sample.

Table 6: MLP Linkage and Sample Selection

<i>Panel A: MLP sample construction</i>					
Year	Eligible	Childhood link	Father identified	Final sample	Final share
1880	1,756,491	1,152,891	1,047,863	864,166	49.2%
1900	2,619,056	1,644,774	1,565,404	1,394,395	53.2%
1920	4,786,523	3,638,704	3,343,024	2,971,796	62.1%
1940	7,393,949	5,903,317	5,491,663	5,022,389	67.9%
<i>Panel B: Full versus linked sample, 1940</i>					
Statistic	Full eligible sample		Final MLP sample		Difference
Agricultural employment share	0.215		0.229		0.014
Mean age	24.556		24.264		-0.291
White share	0.923		0.941		0.018
Urban share	0.536		0.518		-0.017
High-school graduate share	0.381		0.408		0.027
South share	0.290		0.273		-0.016
Valid hourly-earnings share	0.634		0.621		-0.013
Mean log hourly earnings: Agriculture	-1.931		-1.944		-0.013
Variance of log hourly earnings: Agriculture	0.899		0.913		0.015
Mean log hourly earnings: Nonagriculture	-0.778		-0.783		-0.005
Variance of log hourly earnings: Nonagriculture	0.434		0.429		-0.005

Note: Panel A begins with U.S.-born employed men ages 20–29 with a valid current industry. “Childhood link” requires an MLP link to the relevant preceding census, using 1880 as the childhood census for workers observed in 1900 because the 1890 census was destroyed. “Father identified” additionally requires a household-head father in the childhood record, and the final sample additionally requires a valid paternal industry. The final share is relative to the eligible population in the first column. Panel B compares the full eligible population with the final MLP sample in 1940, and the final column reports the linked-sample mean minus the full-sample mean. The hourly-earnings sample requires positive valid wage income, weeks worked, and usual weekly hours; recorded topcoded income of \$5,001 is set to its \$5,000 censoring threshold.

A.1.2. Alternative Historical Linkages

My baseline analysis uses the Multigenerational Longitudinal Panel (MLP) links distributed by IPUMS. As an alternative, I use the Census Tree crosswalks to link each adult observation to his childhood census record and then identify his father as the household head in that census. I also repeat the analysis using the automated linking procedure of [Abramitzky et al. \(2021\)](#), hereafter ABE. My primary ABE results use exact-name conservative links, which require a unique match within a two-year age window, and I additionally report the less restrictive exact-name standard links. I apply the same age, sex, birthplace, employment, industry, earnings, schooling, and geographic restrictions under all linkage procedures.

Appendix Table 7 compares the resulting estimates. The alternative links produce somewhat smaller sector-choice gaps, particularly in 1880 and 1900, but the differences

narrow substantially by 1920 and 1940. The primary ABE estimates are especially close to the Census Tree estimates, while the larger ABE standard sample produces somewhat smaller gaps. The earnings gaps, Fréchet shape parameter, and inherited-skill estimates are also similar across linkage procedures. The inferred inherited-preference parameter is modestly smaller using Census Tree and ABE, but both inherited skills and inherited preferences continue to contribute to sectoral persistence.

Table 7: Robustness to Alternative Historical Linkages

Outcome	Specification	MLP	Census Tree	ABE exact cons.	ABE exact std.
<i>Panel A: Sector choice</i>					
Sector choice, 1880	Unadjusted	0.667	0.594	0.583	0.537
Sector choice, 1880	School + child/adult CZ FE	0.556	0.466	0.468	0.412
Sector choice, 1900	Unadjusted	0.621	0.563	0.545	0.511
Sector choice, 1900	School + child/adult CZ FE	0.499	0.421	0.422	0.375
Sector choice, 1920	Unadjusted	0.558	0.532	0.521	0.488
Sector choice, 1920	School + child/adult CZ FE	0.445	0.416	0.417	0.379
Sector choice, 1940	Unadjusted	0.482	0.457	0.445	0.424
Sector choice, 1940	School + child/adult CZ FE	0.396	0.373	0.367	0.345
<i>Panel B: Log hourly earnings</i>					
Log hourly earnings, Agricultural workers	Unadjusted	-0.677	-0.616	-0.600	-0.530
Log hourly earnings, Nonagricultural workers	Unadjusted	-0.322	-0.316	-0.297	-0.297
Log hourly earnings, Agricultural workers	School + child/adult CZ FE	-0.436	-0.395	-0.399	-0.350
Log hourly earnings, Nonagricultural workers	School + child/adult CZ FE	-0.173	-0.166	-0.165	-0.158
<i>Panel C: Structural parameters</i>					
$\hat{\gamma}$	Unadjusted	2.076	2.053	2.082	2.071
$\hat{\kappa}_A$	Unadjusted	1.604	1.632	1.597	1.585
$\hat{\kappa}_N$	Unadjusted	1.797	1.759	1.685	1.667
$\hat{\tau}$	Unadjusted	0.328	0.295	0.308	0.269
$\hat{\gamma}$	Age + school + adult CZ FE	2.293	2.270	2.302	2.293
$\hat{\kappa}_A$	Age + school + adult CZ FE	1.322	1.340	1.324	1.319
$\hat{\kappa}_N$	Age + school + adult CZ FE	1.433	1.408	1.385	1.363
$\hat{\tau}$	Age + school + adult CZ FE	0.284	0.247	0.257	0.224

Note: The table compares estimates obtained from IPUMS MLP links with estimates obtained from Census Tree and ABE links for the 1870–1880, 1880–1900, 1910–1920, and 1930–1940 census pairs. ABE conservative uses exact-name links that are unique within a two-year age window, while ABE standard uses the less restrictive exact-name procedure. Panel A reports linear-probability coefficients on an indicator for a father employed in agriculture, where the outcome is an indicator for the son working in agriculture. Its adjusted rows absorb childhood-schooling, childhood-commuting-zone, and adulthood-commuting-zone fixed effects. Panel B reports coefficients on father employed in agriculture from regressions of log hourly earnings estimated separately for agricultural and nonagricultural workers in 1940. Its adjusted rows use the same three sets of fixed effects. The Panel B sample has positive hourly earnings and the full-time, full-year restrictions used to estimate γ ; Panel C uses that sample for γ , all observations with positive income, weeks, and hours for earnings levels, and the full eligible linked sample for sector choices. Panel C's unadjusted rows are comparison specifications, not the paper's current benchmark. Its adjusted rows include adult-age and childhood-schooling indicators and adulthood-commuting-zone fixed effects; unlike the current age-and-race-adjusted benchmark, neither Panel C specification adjusts for race.

A.1.3. Persistence Across Schooling, Geography, and Sectors

Figure 7 reports additional schooling and geographic sensitivity specifications complementary to Panel B of Figure 1. The schooling adjustment leaves the parent-sector gap nearly unchanged, while either childhood or adulthood commuting-zone fixed effects attenuate the gap but leave it large throughout 1880–1940.

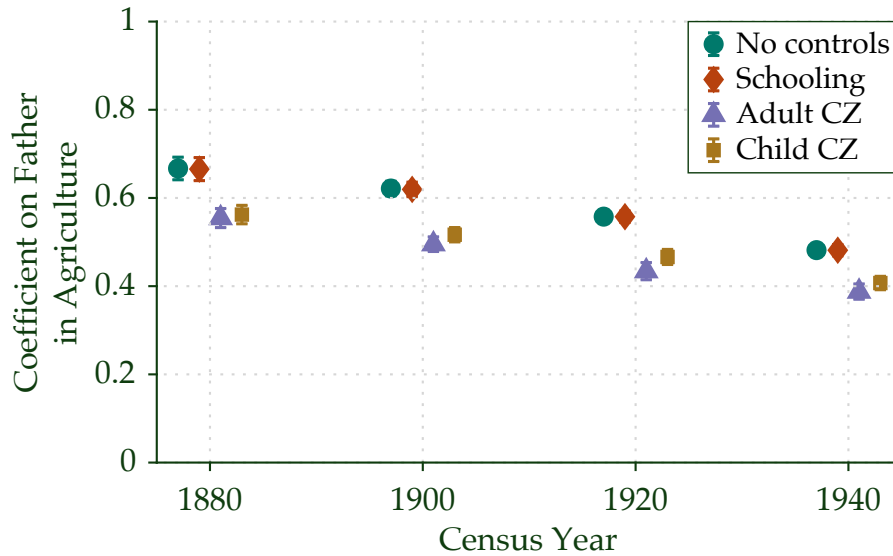


Figure 7: Schooling and Geographic Sensitivity of Agricultural Persistence

Note: Each marker reports the coefficient on an indicator for whether a worker’s father was employed in agriculture from a separate linear probability model whose dependent variable indicates whether the worker was employed in agriculture. The specifications include no additional controls, childhood-school-attendance fixed effects, adulthood commuting-zone fixed effects, or childhood commuting-zone fixed effects. The sample consists of linked U.S.-born employed men aged 20–29 with observed own and paternal industries; agriculture comprises IND1950 codes 100–199. Whiskers denote 95 percent confidence intervals from standard errors clustered by adulthood commuting zone.

Figure 8 compares persistence across sectors. Agricultural employment remains strongly associated with paternal agricultural employment whether the comparison group consists of workers with fathers in manufacturing or services, whereas persistence between manufacturing and services is substantially smaller.

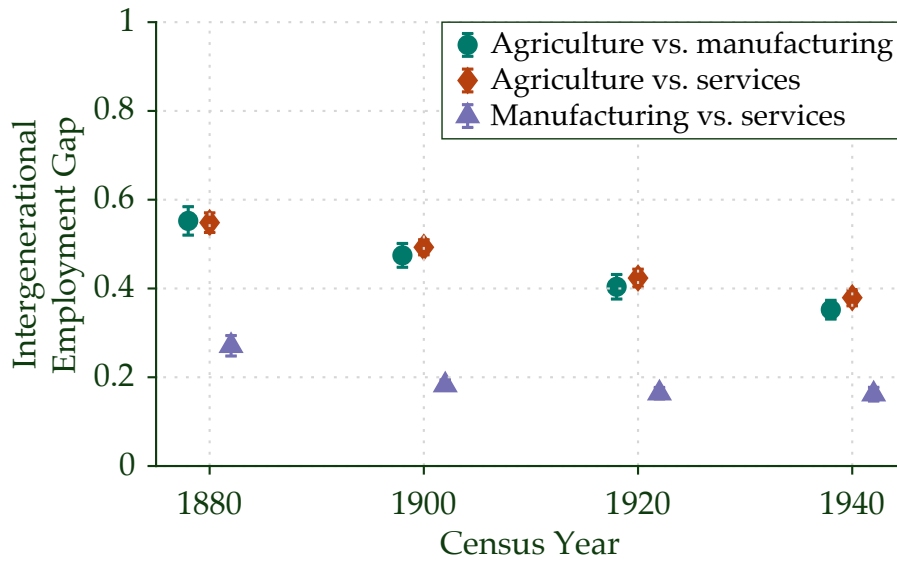


Figure 8: Intergenerational Persistence Across Sectors, 1880–1940

Note: Each marker reports a coefficient from a separate linear probability model estimated in the indicated census year. The agriculture-versus-manufacturing and agriculture-versus-services series report the coefficient on an agricultural-father indicator, restricting the comparison group as indicated; the outcome is agricultural employment. The manufacturing-versus-services series restricts the sample to workers with nonagricultural fathers and reports the coefficient on a manufacturing-father indicator; the outcome is manufacturing employment. Manufacturing comprises IND1950 codes 300–499, and services comprise the remaining nonagricultural industries. All specifications absorb childhood-school-attendance-by-commuting-zone fixed effects; whiskers denote 95 percent confidence intervals from standard errors clustered by adulthood commuting zone.

A.1.4. Detailed Earnings Regressions

Appendix Table 8 reports the estimates and regression diagnostics underlying Figure 2.

Table 8: Earnings Differences by Parental Sector, 1940

	No controls		Baseline		Location	
	Agricultural workers	Nonagricultural workers	Agricultural workers	Nonagricultural workers	Agricultural workers	Nonagricultural workers
Father in agriculture	-0.650*** (0.0307)	-0.304*** (0.0101)	-0.627*** (0.0292)	-0.288*** (0.0089)	-0.433*** (0.0150)	-0.147*** (0.0050)
Age fixed effects	No	No	Yes	Yes	Yes	Yes
Race fixed effects	No	No	Yes	Yes	Yes	Yes
Adult $\times$ child CZ fixed effects	No	No	No	No	Yes	Yes
Observations	363,143	2,756,452	363,143	2,756,452	350,312	2,722,683
R^2	0.074	0.036	0.098	0.118	0.237	0.217

Note: The dependent variable is log hourly wage and salary income, and the reported coefficient corresponds to an indicator for the worker's father being employed in agriculture. Regressions are estimated separately within each destination sector. The middle two columns include age and race fixed effects. The final two columns additionally include fully interacted childhood-by-adulthood commuting-zone fixed effects, assigning a separate fixed effect to each observed commuting-zone pair. None of the specifications controls for childhood schooling; Appendix Table 9 reports the corresponding schooling sensitivity. The sample consists of linked U.S.-born employed men aged 20–29 with observed own and paternal industries, positive wage and salary income, positive weeks worked, and positive usual weekly hours. Standard errors clustered by adulthood commuting zone are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.1.5. Schooling Controls in the Earnings Analysis

Appendix Table 9 assesses whether the main earnings results are sensitive to recorded childhood school attendance. Both specifications include fixed effects for observed pairs of childhood and adult commuting zones; the second additionally absorbs childhood-school-attendance fixed effects.

Table 9: Schooling Sensitivity of Earnings Differences by Parental Sector

	No schooling control		With schooling control	
	Agricultural workers	Nonagricultural workers	Agricultural workers	Nonagricultural workers
Father in agriculture	-0.431*** (0.0151)	-0.143*** (0.0056)	-0.433*** (0.0150)	-0.151*** (0.0055)
Childhood-schooling fixed effects	No	No	Yes	Yes
Adult $\times$ child CZ fixed effects	Yes	Yes	Yes	Yes
Observations	350,312	2,722,683	350,312	2,722,683
R^2	0.231	0.156	0.231	0.162

Note: The dependent variable is log hourly wage and salary income, and the reported coefficient corresponds to an indicator for the worker's father being employed in agriculture. Regressions are estimated separately within each destination sector and include a separate fixed effect for each observed childhood-to-adulthood commuting-zone pair. The final two columns additionally include childhood-school-attendance fixed effects. All four columns use the common sample retained by the schooling-controlled specification. The sample consists of linked U.S.-born employed men aged 20–29 with observed own and paternal industries, positive wage and salary income, positive weeks worked, and positive usual weekly hours. Standard errors clustered by adulthood commuting zone are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Occupation fixed effects. Appendix Table 10 assesses whether the earnings gaps remain after accounting for workers' occupations. Both specifications include fixed effects for observed pairs of childhood and adult commuting zones; the second additionally absorbs worker-occupation fixed effects. The implied earnings discounts attenuate to approximately 29 percent in agriculture and 13 percent in nonagriculture, but remain substantial and statistically significant.

Table 10: Occupation Sensitivity of Earnings Differences by Parental Sector

	No occupation FE		With occupation FE	
	Agricultural workers	Nonagricultural workers	Agricultural workers	Nonagricultural workers
Father in agriculture	-0.431*** (0.0151)	-0.143*** (0.0056)	-0.353*** (0.0137)	-0.130*** (0.0045)
Occupation fixed effects	No	No	Yes	Yes
Adult $\times$ child CZ fixed effects	Yes	Yes	Yes	Yes
Observations	350,277	2,722,452	350,277	2,722,452
R^2	0.231	0.156	0.271	0.252

Note: The dependent variable is log hourly wage and salary income, and the reported coefficient corresponds to an indicator for the worker's father being employed in agriculture. Regressions are estimated separately within each destination sector and include a separate fixed effect for each observed childhood-to-adulthood commuting-zone pair. The final two columns additionally include worker-occupation fixed effects based on OCC1950 codes. All four columns use the common sample retained by the occupation-controlled specification. The sample otherwise follows Table 9. Standard errors clustered by adulthood commuting zone are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2. Labor Supply Parameter Estimates

This appendix provides additional details and robustness checks for the labor-supply parameter estimates in Section 4.1. The complete conditional log-income variance derivation used to identify γ appears in Appendix C.1.1. Here I decompose log-odds persistence between inherited skills and inherited preferences, assess alternative treatments of topcoded earnings, and conclude by considering annual and weekly earnings.

A.2.1. Decomposing Log-Odds Persistence

Equation (ID-4) decomposes the log intergenerational odds ratio additively as

$$\log \mathcal{O} = \underbrace{\gamma (\log \kappa_A + \log \kappa_N)}_{\text{inherited skills}} + \underbrace{-\gamma \log(1 - \tau)}_{\text{inherited preferences}}.$$

I define each mechanism's contribution to persistence as its component divided by $\log \mathcal{O}$. Using $(\hat{\gamma}, \hat{\kappa}_A, \hat{\kappa}_N, \hat{\tau}) = (2.195, 1.497, 1.736, 0.324)$ and $\hat{\mathcal{O}} = 19.270$ gives

$$\hat{s}_\kappa = \frac{\hat{\gamma}(\log \hat{\kappa}_A + \log \hat{\kappa}_N)}{\log \hat{\mathcal{O}}} = 0.709, \quad \hat{s}_\tau = \frac{-\hat{\gamma} \log(1 - \hat{\tau})}{\log \hat{\mathcal{O}}} = 0.291.$$

Thus inherited skills account for 70.9 percent of observed log-odds persistence and inherited preferences account for the remaining 29.1 percent.

A.2.2. Inherited Skills and Preferences among Movers

The main estimates may partly reflect systematic differences in the local labor markets occupied by ag-born and nonag-born workers or advantages conferred by local family networks. To assess this concern, I repeat the location procedure among workers whose adult commuting zone differs from their childhood commuting zone. The Movers column of Table 11 uses mover-specific hourly-earnings moments and sector-choice probabilities, while retaining the location estimate of the Fréchet shape parameter. The inherited-skill and inherited-preference estimates become smaller, but remain economically meaningful among movers.

Table 11: Inherited Skills and Preferences among Movers

	Baseline	Location	Movers
<i>Panel A: Estimated Intergenerational Persistence</i>			
Inherited Skills, $\hat{\kappa}_A$	1.497	1.306	1.176
Inherited Skills, $\hat{\kappa}_N$	1.736	1.422	1.263
Inherited Preferences, $\hat{\tau}$	0.324	0.284	0.147
<i>Panel B: Mean hourly earnings</i>			
Agriculture, ag-born: $\hat{y}_A(A)$	0.19	0.20	0.22
Agriculture, nonag-born: $\hat{y}_A(N)$	0.36	0.32	0.29
Nonagriculture, ag-born: $\hat{y}_N(A)$	0.48	0.52	0.54
Nonagriculture, nonag-born: $\hat{y}_N(N)$	0.60	0.59	0.61
<i>Panel C: Intergenerational persistence</i>			
Ag. employment share, ag-born	0.529	0.471	0.321
Ag. employment share, nonag-born	0.055	0.089	0.116
Sector-choice odds ratio	19.270	9.122	3.626

Note: The Baseline and Location columns reproduce the corresponding hourly-earnings estimates in Table 2. The Movers column applies the Location procedure to workers whose adult and childhood commuting zones differ, using mover-specific earnings and sector-choice moments and the Location estimate of γ . All columns adjust the earnings means and sector-choice probabilities for age and race fixed effects; Location and Movers additionally include adult commuting-zone fixed effects. Earnings moments use workers with valid positive hourly earnings; sector-choice moments entering κ_j , τ , and Panel C use the full linked sample for the relevant column.

A.2.3. Alternative Skill Distributions

Table 12 compares the baseline Fréchet specification with a bivariate lognormal distribution and a bivariate Fréchet distribution joined by a Frank copula. In every specification, the bivariate object is the pair of agricultural and nonagricultural skills, (ϵ_A, ϵ_N) , rather than skills indexed by parental origin. Ag-born and nonag-born workers draw from the same joint distribution; parental origin affects sectoral payoffs only through κ_A , κ_N , and τ .

The baseline specification assumes independent unit-scale Fréchet skills with a common shape parameter:

$$F_j(\epsilon) \equiv \Pr(\epsilon_j \leq \epsilon) = \exp(-\epsilon^{-\gamma}), \quad \epsilon > 0, \quad j \in \{A, N\}, \quad \epsilon_A \perp \epsilon_N. \quad (12)$$

The bivariate lognormal specification instead assumes

$$\begin{pmatrix} \log \epsilon_A \\ \log \epsilon_N \end{pmatrix} \sim \mathcal{N} \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_A^2 & \rho \sigma_A \sigma_N \\ \rho \sigma_A \sigma_N & \sigma_N^2 \end{pmatrix} \right]. \quad (13)$$

Finally, the Fréchet–Frank specification allows sector-specific Fréchet marginals,

$$F_j(\epsilon) = \exp(-\epsilon^{-\gamma_j}), \quad j \in \{A, N\}, \quad (14)$$

and joins them using the Frank copula

$$\begin{aligned} \Pr(\epsilon_A \leq a, \epsilon_N \leq n) &= C_{\theta_F}(F_A(a), F_N(n)), \\ C_{\theta}(u, v) &= -\frac{1}{\theta} \log \left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1} \right]. \end{aligned} \quad (15)$$

for $\theta \neq 0$, with $C_0(u, v) = uv$ denoting independence. All marginal location or scale parameters are normalized because the relative sector payoff R absorbs their relative level.

I estimate every specification by simulated method of moments using the same seven targets. These consist of the pooled within-cell variance of log earnings, the agricultural employment shares of ag-born and nonag-born workers, the two within-sector parental-origin earnings ratios, and the variances of log earnings among ag-born and nonag-born workers employed in nonagriculture. The five-parameter baseline Fréchet model is overidentified, while the two bivariate specifications each have seven parameters and are exactly identified by these moments.

Table 12: SMM Estimates under Alternative Skill Distributions

	Fréchet	Bivariate lognormal	Fréchet–Frank
<i>Panel A: Skill distribution</i>			
Common shape, γ	2.097		
Agricultural log-skill dispersion, σ_A		0.872	
Nonagricultural log-skill dispersion, σ_N		0.604	
Log-skill correlation, ρ		0.724	
Agricultural shape, γ_A			1.438
Nonagricultural shape, γ_N			2.244
Frank copula parameter, θ_F			1.599
<i>Panel B: Intergenerational persistence</i>			
Inherited Skills, κ_A	1.586	1.122	2.719
Inherited Skills, κ_N	1.800	1.234	1.611
Inherited Preferences, τ	0.325	0.503	0.253
Relative sector payoff, R	2.204	2.146	3.614
<i>Panel C: Estimation</i>			
SMM objective	0.080	0.085	0.036
Targeted moments	7	7	7
Converged	Yes	Yes	Yes

Note: All specifications minimize an identity-weighted quadratic form in the same seven log moment deviations using fixed common random numbers. The Fréchet column imposes a common shape parameter and independence across sectoral skills. The bivariate lognormal allows sector-specific log-skill dispersions and correlation ρ ; the Fréchet–Frank specification allows sector-specific shape parameters and dependence governed by the Frank copula parameter θ_F . The relative sector payoff R is a nuisance parameter. Reported results use 200,000 simulation draws and multiple starting values.

A.2.4. Allocation-Based Elasticity Illustration

As a complementary illustration of the model’s distinction between aggregate and within-group labor-supply elasticities, I estimate the response of aggregate sectoral allocation to relative earnings using 1940–1950 commuting-zone-by-industry variation. For broad nonagricultural industries j , I estimate

$$\Delta \log \left(\frac{\phi_{j,r}}{\phi_{A,r}} \right) = \beta \Delta \log \left(\frac{y_{j,r}}{y_{A,r}} \right) + \alpha_{j,d(r)} + u_{j,r},$$

where r indexes commuting zones and $\alpha_{j,d(r)}$ denotes industry-by-Census-division fixed effects. The sample stacks seven broad nonagricultural industries, while agriculture is the common reference sector. I instrument relative earnings growth with a leave-one-

commuting-zone-out shift-share measure,

$$Z_{j,r} = s_{j,r,1940}g_{j,-r} - s_{A,r,1940}g_{A,-r},$$

where $s_{j,r,1940}$ is industry j 's initial CZ employment share and $g_{j,-r}$ is national 1940–1950 employment growth excluding CZ r . The instrument therefore varies across both commuting zones and industries rather than assigning every industry within a CZ the same shock.

Table 13 reports the resulting aggregate elasticities and applies the aggregation relationship in Proposition 1 using the observed 1940 and 1950 parental composition and subgroup agricultural shares. The population-weighted estimate is $\hat{\beta} = 1.067$. The corresponding implied within-group elasticity is 1.533 using the 1940 shares and 1.422 using the 1950 shares, approximately one-third above the unadjusted aggregate elasticity. The unweighted estimates imply a smaller within-group elasticity near one. Because the regression stacks comparisons of each nonagricultural industry with agriculture, whereas the proposition is exact for the aggregate two-sector margin, I interpret this exercise as an illustration of the attenuation mechanism rather than as an alternative preferred estimator of γ .

Table 13: Aggregate Reallocation Elasticity Estimates

	(1)	(2)
	Unweighted	Population weighted
Aggregate elasticity $\hat{\beta}$	0.716 (0.284)	1.067 (0.334)
First-stage F -statistic	24.21	30.17
Industry–CZ observations	2,423	2,423
CZ clusters	536	536
Industry $\times$ division FE	Yes	Yes

Note: The dependent variable is the 1940–1950 change in log employment share in nonagricultural industry j relative to agriculture. Relative mean hourly earnings growth is instrumented with the leave-one-CZ-out shift-share measure defined above. Employment shares and national employment growth use full-count records, while 1950 earnings moments apply the Census sample-line weights. Both columns include industry-by-Census-division fixed effects; column 2 weights observations by the CZ population of U.S.-born men ages 20–29 in 1940. Standard errors, clustered by commuting zone, are reported in parentheses.

A.2.5. Adjustment for Topcoded Earnings

The main text retains the variance-based estimator but checks its sensitivity to replacing each topcoded annual income with a multiple of the \$5,000 censoring threshold. In the final variance-estimation sample, 2,164 of 2,077,253 workers (0.104 percent) are topcoded, and their capped observations account for 0.501 percent of total wage and salary income. I calibrate the multiplier to 2.926 so that these workers instead account for 1.452 percent of total income, the 1940 income share of the top 0.1 percent reported by [Atkinson, Piketty and Saez \(2011\)](#). I then reconstruct hourly earnings and reestimate γ from the residual variance on the fixed main-text sample.

Table 14 shows that the estimate changes little over a broad range of multipliers. At the calibrated value, $\hat{\gamma}$ declines from 2.195 to 2.180, while the quantile RMSE rises only from 0.322 to 0.325.

Table 14: Sensitivity to the Topcode Adjustment

Topcode multiplier	Topcoded income share (%)	$\hat{\gamma}$	Observations	Quantile RMSE
1.00	0.501	2.195	2,077,253	0.322
1.25	0.625	2.193	2,077,253	0.323
1.50	0.749	2.190	2,077,253	0.323
1.75	0.873	2.188	2,077,253	0.324
2.00	0.997	2.186	2,077,253	0.324
2.93	1.452	2.180	2,077,253	0.325

Note: Each row replaces topcoded annual income with the stated multiple of \$5,000 before constructing hourly earnings and reestimating γ . The 2.93 multiplier matches the 1.452 percent target share; quantile RMSE is measured over the 1st–99th residual percentiles.

Table 15 applies the calibrated topcode adjustment to the estimates of inherited skills and preferences. The estimates are nearly unchanged from the baseline, so I treat the adjustment as a robustness exercise rather than a separate main specification.

Table 15: Inherited Skills and Preferences: Topcode Robustness

	Baseline	Location	Topcode Adjusted
Inherited Skills, $\hat{\kappa}_A$	1.497 (0.033)	1.306 (0.020)	1.508 (0.033)
Inherited Skills, $\hat{\kappa}_N$	1.736 (0.027)	1.422 (0.022)	1.740 (0.027)
Inherited Preferences, $\hat{\tau}$	0.324 (0.020)	0.284 (0.013)	0.324 (0.020)

Note: The first two columns reproduce the main estimates in Table 2. The Topcode Adjusted column replaces topcoded income with 2.926 times the censoring threshold when estimating γ , while holding the baseline earnings and sector-choice moments fixed. Commuting-zone cluster-bootstrap standard errors based on 499 resamples are reported in parentheses.

A.2.6. Visualization of Empirical vs Model Distribution

For a visual check, Figure 9 compares the residual earnings distribution with the log-Fréchet densities implied by the baseline and topcode-adjusted estimates.

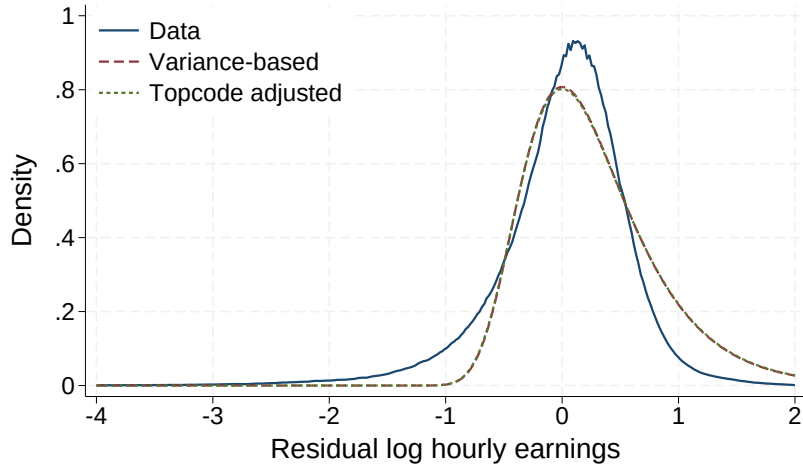


Figure 9: Residual Earnings Distribution in Data and Model

Notes: The solid line plots the kernel density of residual log hourly wage and salary income after removing worker-sector-by-parental-sector, age, and race fixed effects. The dashed red and short-dashed green lines use the baseline and topcode-adjusted estimates, $\hat{\gamma} = 2.195$ and 2.180 , respectively. The estimation sample has positive wage and salary income, at least 40 weeks worked, and at least 35 usual weekly hours, with no log-earnings restriction; the figure displays residuals between -4 and 2 .

A.2.7. Alternative Earnings Measures

Hourly earnings are the closest empirical counterpart to the model's wage per efficiency unit, but they inherit measurement error from both weeks and hours. Annual and weekly earnings provide useful checks on whether this additional measurement affects the estimated dispersion of earnings. For comparability, Table 16 estimates all three concepts on the common preferred sample used in the main text.

Table 16: Variance-Based Estimates of the Fréchet Shape Parameter by Income Measure

	Annual		Weekly		Hourly	
	Baseline	Location	Baseline	Location	Baseline	Location
$\hat{\gamma}$	2.337	2.451	2.362	2.477	2.195	2.319
Residual SD of log wages	0.549	0.523	0.543	0.518	0.584	0.553
Observations	2,077,253	2,077,253	2,077,253	2,077,253	2,077,253	2,077,253
Topcoded observations	2,164	2,164	2,164	2,164	2,164	2,164
Topcoded share (%)	0.104	0.104	0.104	0.104	0.104	0.104
Earnings regression R^2	0.393	0.448	0.391	0.446	0.411	0.472

Note: Estimates use $\hat{\gamma} = \pi/(\sqrt{6}\hat{\sigma})$ after removing worker-sector-by-parental-sector, age, and race effects; Location columns additionally control for adult commuting zone. Weekly earnings divide annual wage and salary income by weeks worked, and hourly earnings additionally divide by usual weekly hours. All columns use the common unrestricted 2,077,253-observation sample defined in Table 1.

The estimates are similar across earnings concepts in both the baseline and location specifications. Figure 10 shows the corresponding distributional fits.

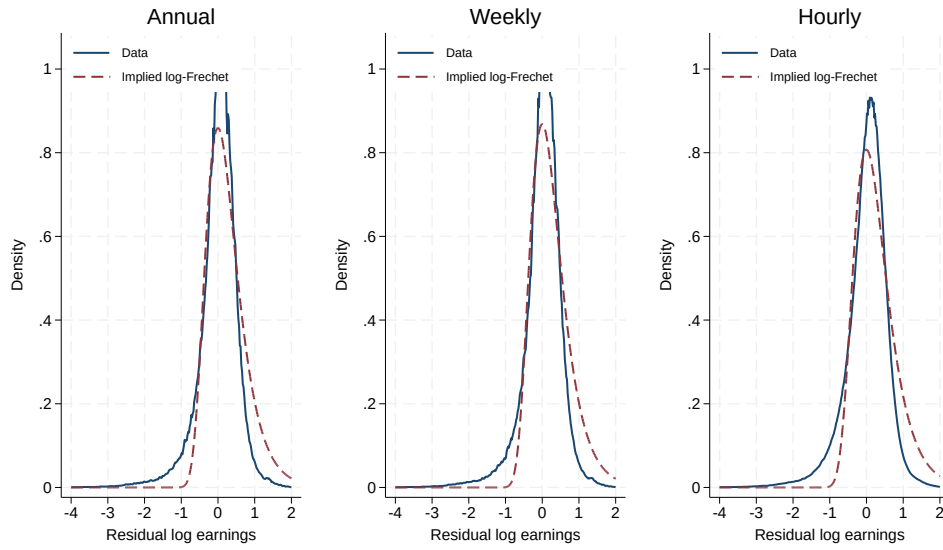


Figure 10: Residual Earnings Distributions and Implied Log-Fréchet Densities by Income Measure

Note: The solid lines plot kernel densities of residual log earnings after removing worker-sector-by-parental-sector, age, and race fixed effects. Dashed lines plot the log-Fréchet densities implied by the baseline estimates in Table 16. Panels use the common unrestricted estimation sample and display residuals between -4 and 2 .

Finally, Table 17 carries each variance-based estimate of γ through the parameter calculations. The estimated inherited skills and preferences remain economically important across earnings concepts and control sets, although their magnitudes vary with the dispersion estimate and adjusted income gaps.

Table 17: Inherited Skills and Preferences by Income Measure

	Annual earnings		Weekly earnings		Hourly earnings	
	Baseline	Location	Baseline	Location	Baseline	Location
<i>Panel A: Estimated Intergenerational Persistence</i>						
Inherited Skills, $\hat{\kappa}_A$	1.787	1.613	1.640	1.472	1.497	1.306
Inherited Skills, $\hat{\kappa}_N$	1.754	1.467	1.694	1.416	1.736	1.422
Inherited Preferences, $\hat{\tau}$	0.117	0.040	0.207	0.146	0.324	0.284
<i>Panel B: Mean earnings</i>						
Agriculture, ag-born: $\hat{y}_A(A)$	330.46	347.96	8.72	9.19	0.19	0.20
Agriculture, nonag-born: $\hat{y}_A(N)$	486.90	426.04	13.86	12.24	0.36	0.32
Nonagriculture, ag-born: $\hat{y}_N(A)$	702.00	762.78	17.68	19.23	0.48	0.52
Nonagriculture, nonag-born: $\hat{y}_N(N)$	913.76	896.53	22.30	21.86	0.60	0.59
<i>Panel C: Intergenerational persistence</i>						
Sector-choice odds ratio	19.270	9.122	19.270	9.122	19.270	9.122

Note: Each column uses the corresponding estimate of γ in Table 16. All columns adjust income and sector-choice moments for age and race; Location columns additionally adjust for adult commuting zone. Earnings moments use the relevant income sample; all sector-choice moments entering κ_j , τ , and Panel C use the full linked sample, as in Table 2.

B. Appendix: Theoretical Results

B.1. Proofs and Supporting Derivations for the Model

This appendix provides the proofs of Propositions 1, 2, 3, and 4. Throughout the general equilibrium derivations, I suppress time subscripts. All derivatives are evaluated at the common stationary employment share, $\bar{\phi}_A$, before the technological improvement.

B.1.1. Aggregate Labor Supply Elasticity

Proof of Proposition 1. Holding parental composition and common benefits fixed, equation (1) implies

$$\frac{\partial \phi_{A,t}(k)}{\partial \log(w_{N,t}/w_{A,t})} = -\gamma \phi_{A,t}(k) \phi_{N,t}(k).$$

Aggregating across parental groups gives

$$\frac{\partial \phi_{A,t}}{\partial \log(w_{N,t}/w_{A,t})} = -\gamma \sum_{k \in \{A,N\}} \phi_{k,t-1} \phi_{A,t}(k) \phi_{N,t}(k).$$

Since $\phi_{N,t} = 1 - \phi_{A,t}$, the aggregate relative sectoral labor supply elasticity satisfies

$$\mathcal{E}_t = \gamma \cdot \frac{\sum_{k \in \{A,N\}} \phi_{k,t-1} \phi_{A,t}(k) \phi_{N,t}(k)}{\phi_{A,t} \phi_{N,t}}.$$

The law of total variance for $D_{i,t} = \mathbb{1}(s_{i,t} = A)$ gives

$$\text{Var}(D_{i,t}) = \mathbb{E}[\text{Var}(D_{i,t} | k)] + \text{Var}(\mathbb{E}[D_{i,t} | k]),$$

where

$$\text{Var}(D_{i,t}) = \phi_{A,t} \phi_{N,t} \quad \text{and} \quad \mathbb{E}[\text{Var}(D_{i,t} | k)] = \sum_{k \in \{A,N\}} \phi_{k,t-1} \phi_{A,t}(k) \phi_{N,t}(k).$$

Consequently,

$$\mathcal{E}_t = \gamma \left[1 - \frac{\text{Var}(\mathbb{E}[D_{i,t} | k])}{\text{Var}(D_{i,t})} \right].$$

The conditional choice probabilities lie strictly between zero and one, so $\mathcal{E}_t > 0$. The between-group variance is nonnegative, implying $\mathcal{E}_t \leq \gamma$, with strict inequality when both parental groups are present and have different sector-choice probabilities. For two parental groups, the between-group variance equals

$$\text{Var}(\mathbb{E}[D_{i,t} | k]) = \phi_{A,t-1} (1 - \phi_{A,t-1}) [\phi_{A,t}(A) - \phi_{A,t}(N)]^2.$$

Under stationarity, equation (3) therefore yields

$$\mathcal{E}_t = \gamma [1 - [\phi_{A,t}(A) - \phi_{A,t}(N)]^2].$$

The same expressions apply to the elasticity with respect to relative common nonpecuniary benefits because workers' sector choices depend on the product $(B_{N,t}/B_{A,t})(w_{N,t}/w_{A,t})$.

□

B.1.2. Immediate General Equilibrium Response

Let $\bar{\phi}_N = 1 - \bar{\phi}_A$ denote the common stationary employment share in nonagriculture. To simplify the comparison across economies, let $g \equiv \phi_A(A) - \phi_A(N)$ denote the gap between the agricultural employment shares of ag-born and nonag-born workers. Stationarity and

equation (3) imply

$$\phi_A(A) = \bar{\phi}_A + \bar{\phi}_N g, \quad \phi_A(N) = \bar{\phi}_A(1 - g), \quad (16)$$

with $\phi_N(k) = 1 - \phi_A(k)$ for both parental groups. The no-IGP economy has $g = 0$, while the two IGP economies have the same positive g by Assumption 1.

The aggregate effective labor supplies satisfy

$$\begin{aligned} H_A &= \bar{\gamma} [\bar{\phi}_A \kappa_A \phi_A(A)^{1-1/\gamma} + \bar{\phi}_N \phi_A(N)^{1-1/\gamma}], \\ H_N &= \bar{\gamma} [\bar{\phi}_A \phi_N(A)^{1-1/\gamma} + \bar{\phi}_N \kappa_N \phi_N(N)^{1-1/\gamma}]. \end{aligned} \quad (17)$$

Holding parental composition fixed, the group-specific sector-choice equations imply

$$\frac{\partial \phi_A}{\partial \log(w_N/w_A)} = -\gamma \bar{\phi}_A \bar{\phi}_N (1 - g^2). \quad (18)$$

Differentiating aggregate effective labor supply with respect to the relative wage yields

$$\begin{aligned} & -\frac{1}{\gamma - 1} \frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)} \\ &= 1 - g \left[\frac{\bar{\phi}_A \phi_A(A) h_A(A)}{H_A} - \frac{\bar{\phi}_A \phi_N(A) h_N(A)}{H_N} \right]. \end{aligned} \quad (19)$$

The two fractions inside the brackets are the shares of effective agricultural and nonagricultural labor supplied by ag-born workers, respectively. Thus, even when the two IGP economies have identical worker allocations, their wage feedbacks can differ because inherited skills change these effective-labor shares.

Under homothetic demand, goods-market clearing, sectoral production, and competitive wages imply

$$d \log \left(\frac{w_N}{w_A} \right) = \frac{1 - \sigma}{\sigma} d \log Z_A + \frac{1}{\sigma} d \log \left(\frac{H_A}{H_N} \right), \quad (20)$$

where all fundamentals other than Z_A are fixed. Combining this condition with (18) gives the immediate employment response:

$$-\frac{d \phi_A}{d \log Z_A} = \frac{\gamma \bar{\phi}_A \bar{\phi}_N (1 - g^2) (1 - \sigma)}{\sigma - \frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)}} > 0. \quad (21)$$

The denominator is positive because an increase in the relative wage of nonagriculture reduces relative agricultural effective labor supply.

Proof of Proposition 2. In the no-IGP economy, $g = 0$ and the derivative in (19) equals $-(\gamma - 1)$. Consequently,

$$-\frac{d\phi_A}{d\log Z_A}\Big|_{\text{no-IGP}} = \frac{\gamma\bar{\phi}_A\bar{\phi}_N(1-\sigma)}{\sigma + \gamma - 1}.$$

Consider next the two economies with intergenerational persistence. They have the same g and therefore the same numerator in (21). Relative to the τ -IGP economy, inherited skills increase the fraction of effective agricultural labor supplied by ag-born workers and decrease their fraction of effective nonagricultural labor. Equation (19) therefore implies

$$-\frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)}\Big|_{\kappa\text{-IGP}} < -\frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)}\Big|_{\tau\text{-IGP}}.$$

Thus, the τ -IGP economy has the stronger wage feedback and the smaller immediate reallocation response.

It remains to show that the κ -IGP economy reallocates less than the no-IGP economy. In the κ -IGP economy, symmetric inherited skills and the matched sector-choice gap imply

$$\kappa^{2\gamma} = \frac{\phi_A(A)\phi_N(N)}{\phi_A(N)\phi_N(A)}, \quad \kappa \equiv \kappa_A = \kappa_N. \quad (22)$$

The following short calculation establishes the required bound on effective-labor shares. For this calculation alone, define the common odds multiplier

$$\rho \equiv \left[\frac{\phi_A(N)\phi_N(N)}{\phi_A(A)\phi_N(A)} \right]^{1/(2\gamma)}.$$

Using stationarity and (22), the two effective-labor shares in (19) can be written as

$$\frac{\bar{\phi}_A\phi_A(A)h_A(A)}{H_A} = \frac{\rho\phi_A(A)}{1 + (\rho - 1)\phi_A(A)}, \quad \frac{\bar{\phi}_A\phi_N(A)h_N(A)}{H_N} = \frac{\rho\phi_A(N)}{1 + (\rho - 1)\phi_A(N)}.$$

Their difference is therefore

$$\frac{\rho g}{[1 + (\rho - 1)\phi_A(A)][1 + (\rho - 1)\phi_A(N)]}.$$

The stationary relations imply

$$\begin{aligned}\phi_A(A) + \phi_A(N) - 1 &= (2\bar{\phi}_A - 1)(1 - g), \\ \phi_A(N)\phi_N(N) - \phi_A(A)\phi_N(A) &= (2\bar{\phi}_A - 1)g(1 - g).\end{aligned}$$

Thus, $\rho - 1$ and $\phi_A(A) + \phi_A(N) - 1$ have the same sign. It follows that

$$\begin{aligned}[1 + (\rho - 1)\phi_A(A)][1 + (\rho - 1)\phi_A(N)] - \rho \\ = (\rho - 1)[\phi_A(A) + \phi_A(N) - 1 + (\rho - 1)\phi_A(A)\phi_A(N)] \geq 0.\end{aligned}$$

Consequently, the difference between the two effective-labor shares is no greater than g . By (19), this implies

$$-\frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)} \Big|_{\kappa\text{-IGP}} \geq (\gamma - 1)(1 - g^2).$$

Since $g > 0$ and $\sigma > 0$,

$$\sigma + (\gamma - 1)(1 - g^2) > (1 - g^2)(\sigma + \gamma - 1).$$

Substitution into (21) establishes that the no-IGP economy reallocates strictly more workers than the κ -IGP economy. Combining the two comparisons establishes Proposition 2. □

B.1.3. Dynamic Transmission Across Generations

To examine intergenerational transmission, differentiate the next generation's employment law of motion with respect to the previous generation's agricultural employment share. Holding the next generation's wages fixed gives

$$\frac{\partial \phi_{A,t+1}}{\partial \phi_{A,t}} \Big|_{w_{N,t+1}/w_{A,t+1}} = \phi_{A,t+1}(A) - \phi_{A,t+1}(N) = g.$$

The two IGP economies have the same positive direct effect, whereas the no-IGP economy has no direct effect.

Changes in parental composition also change the relative effective labor supplied to

agriculture, holding wages fixed:

$$\begin{aligned} & \left. \frac{\partial \log(H_A/H_N)}{\partial \phi_{A,t-1}} \right|_{w_N/w_A} \\ &= \frac{\phi_A(A)h_A(A) - \phi_A(N)h_A(N)}{H_A} - \frac{\phi_N(A)h_N(A) - \phi_N(N)h_N(N)}{H_N}. \end{aligned} \quad (23)$$

Combining this expression with (20) and (18) gives the total dynamic response:

$$\frac{d\phi_{A,t+1}}{d\phi_{A,t}} = g - \frac{\gamma \bar{\phi}_A \bar{\phi}_N (1 - g^2)}{\sigma - \frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)}} \left. \frac{\partial \log(H_A/H_N)}{\partial \phi_{A,t-1}} \right|_{w_N/w_A}. \quad (24)$$

The first term captures the direct effect of changing parental composition, while the second captures the opposing effect of the induced relative-wage adjustment.

To establish the sign of the dynamic response in the inherited-preferences economy, I use the following concavity inequality.

Lemma 1. *Under Assumption 1, when $\kappa_A = \kappa_N = 1$ and $g > 0$,*

$$g \left[-\frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)} \right] > \gamma \bar{\phi}_A \bar{\phi}_N (1 - g^2) \left. \frac{\partial \log(H_A/H_N)}{\partial \phi_{A,t-1}} \right|_{w_N/w_A}.$$

Proof. Let $f(x) = x^{1-1/\gamma}$, which is strictly concave because $\gamma > 1$. The stationary relations imply

$$\begin{aligned} \phi_A(A)\phi_N(N) - \phi_A(N)\phi_N(A) &= g, \\ \phi_A(A)\phi_N(A) &= \phi_A(N)\phi_N(A) + g\phi_N(A), \\ \phi_A(N)\phi_N(N) &= \phi_A(N)\phi_N(A) + g\phi_A(N). \end{aligned}$$

Thus, the final two products lie strictly between $\phi_A(N)\phi_N(A)$ and $\phi_A(A)\phi_N(N)$. For any $x < y < z$, strict concavity implies

$$\frac{f(y) - f(x)}{y - x} > \frac{f(z) - f(x)}{z - x} > \frac{f(z) - f(y)}{z - y}.$$

Applying these inequalities at the two intermediate products, using $xf'(x) = (1-1/\gamma)f(x)$,

and collecting terms gives

$$\begin{aligned} & \left(1 - \frac{1}{\gamma}\right) g \left\{ \bar{\phi}_A^2 f[\phi_A(A)\phi_N(A)] + \bar{\phi}_N^2 f[\phi_A(N)\phi_N(N)] \right. \\ & \quad \left. + \bar{\phi}_A \bar{\phi}_N [(1-g)f[\phi_A(A)\phi_N(N)] + (1+g)f[\phi_A(N)\phi_N(A)]] \right\} \\ & > \bar{\phi}_A \bar{\phi}_N (1-g^2) \{ f[\phi_A(A)\phi_N(N)] - f[\phi_A(N)\phi_N(A)] \}. \end{aligned}$$

The expression inside braces on the left is equal to

$$\frac{H_A H_N}{\bar{\gamma}^2} - \bar{\phi}_A \bar{\phi}_N g \{ f[\phi_A(A)\phi_N(N)] - f[\phi_A(N)\phi_N(A)] \}.$$

Rearranging therefore yields

$$\begin{aligned} & (\gamma - 1) g \frac{H_A H_N}{\bar{\gamma}^2} \\ & > \bar{\phi}_A \bar{\phi}_N (\gamma - g^2) \{ f[\phi_A(A)\phi_N(N)] - f[\phi_A(N)\phi_N(A)] \}. \end{aligned}$$

Substituting the effective labor expressions into the derivatives in (19) and (23) shows that this last inequality is equivalent to the claim of the lemma. $\square$

Proof of Proposition 3. In the no-IGP economy, $g = 0$ and changes in parental composition leave relative effective labor unchanged. Consequently, (24) gives $d\phi_{A,t+1}/d\phi_{A,t} = 0$.

In the τ -IGP economy, Lemma 1 implies

$$\begin{aligned} & g \left[\sigma - \frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)} \right] \\ & > \gamma \bar{\phi}_A \bar{\phi}_N (1-g^2) \frac{\partial \log(H_A/H_N)}{\partial \phi_{A,t-1}} \Big|_{w_N/w_A}, \end{aligned}$$

where the inequality is strict because $\sigma > 0$ and $g > 0$. Since the denominator in (24) is positive, the total dynamic response is strictly positive.

In the κ -IGP economy, the direct effect remains positive, but the wage adjustment can dominate it. The weak-persistence expansion in the next subsection establishes that the dynamic response is negative for sufficiently small $g > 0$. As g approaches one, the group-specific agricultural employment shares approach one and zero, respectively, and the symmetric inherited skill advantage diverges. In this limit, (19) implies that the wage

feedback tends to zero, while (23) tends to $1/(\bar{\phi}_A \bar{\phi}_N)$. Equation (24) therefore implies that the dynamic response tends to one. Hence, the total dynamic effect in the κ -IGP economy can have either sign. $\square$

B.1.4. Cumulative Effects with Weak Intergenerational Persistence

I now examine how the immediate and dynamic effects combine when intergenerational persistence is sufficiently weak. These results concern local responses to a permanent improvement in agricultural technology around the initial stationary equilibrium. For each stylized economy, let $\mathcal{R}_h$ denote the increase in the nonagricultural employment share h generations after the shock, per unit increase in $\log Z_A$. Let $\mathcal{R}_0 = -d\phi_A/d\log Z_A > 0$ denote the immediate response and let $\lambda = d\phi_{A,t+1}/d\phi_{A,t}$ denote the dynamic transmission coefficient.

For a permanent technological improvement, linearization around the stationary equilibrium implies

$$\mathcal{R}_h = \mathcal{R}_0 (1 + \lambda + \dots + \lambda^h), \quad h = 0, 1, 2, \dots \quad (25)$$

Each generation experiences the same direct effect of the technological improvement, together with the employment response inherited from the previous generation. If $|\lambda| < 1$, the eventual response is

$$\mathcal{R}_\infty = \frac{\mathcal{R}_0}{1 - \lambda}. \quad (26)$$

Because $\lambda = 0$ in the no-IGP economy, intergenerational persistence increases eventual reallocation relative to this benchmark if and only if

$$\lambda > 1 - \frac{\mathcal{R}_0}{\mathcal{R}_0^{\text{no-IGP}}}. \quad (27)$$

Thus, dynamic propagation must be sufficiently strong to overcome the initial dampening of reallocation.

Proof of Proposition 4. Fix the common interior stationary agricultural employment share, and let $g > 0$ denote the parental-sector employment gap. I examine the limit as g approaches zero, holding the other model parameters fixed. At $g = 0$, the two persistence

economies converge to the no-IGP economy. Stationarity implies

$$\begin{aligned}\phi_A(A) &= \bar{\phi}_A + \bar{\phi}_N g, \\ \phi_A(N) &= \bar{\phi}_A(1 - g), \\ \phi_N(A) &= \bar{\phi}_N(1 - g), \\ \phi_N(N) &= \bar{\phi}_N + \bar{\phi}_A g.\end{aligned}$$

When persistence arises exclusively from inherited preferences, a first-order expansion of (23) gives

$$\left. \frac{\partial \log(H_A/H_N)}{\partial \phi_{A,t-1}} \right|_{\tau\text{-IGP}} = \frac{\gamma - 1}{\gamma} \cdot \frac{g}{\bar{\phi}_A \bar{\phi}_N} + O(g^2). \quad (28)$$

For symmetric inherited skills, the matched sector-choice gap implies

$$\log \kappa = \frac{1}{2\gamma} \log \left[\frac{\phi_A(A)\phi_N(N)}{\phi_A(N)\phi_N(A)} \right] = \frac{g}{2\gamma \bar{\phi}_A \bar{\phi}_N} + O(g^2).$$

Substituting this expression into the same effective labor derivative gives

$$\left. \frac{\partial \log(H_A/H_N)}{\partial \phi_{A,t-1}} \right|_{\kappa\text{-IGP}} = \frac{g}{\bar{\phi}_A \bar{\phi}_N} + O(g^2). \quad (29)$$

In both economies, the relative effective labor response to wages satisfies

$$-\frac{\partial \log(H_A/H_N)}{\partial \log(w_N/w_A)} = (\gamma - 1) + O(g^2).$$

Consequently, the immediate response in (21) satisfies

$$\frac{\mathcal{R}_0^r}{\mathcal{R}_0^{\text{no-IGP}}} = 1 + O(g^2), \quad r \in \{\kappa\text{-IGP}, \tau\text{-IGP}\}. \quad (30)$$

Substituting the two parental-composition derivatives into (24) yields

$$\begin{aligned}\lambda^{\tau\text{-IGP}} &= \frac{\sigma}{\sigma + \gamma - 1} g + O(g^2), \\ \lambda^{\kappa\text{-IGP}} &= -\frac{1 - \sigma}{\sigma + \gamma - 1} g + O(g^2).\end{aligned} \quad (31)$$

Thus, the immediate dampening from intergenerational persistence is second order in the sector-choice gap, while the dynamic transmission is first order. For any fixed $h \geq 1$, (25)

therefore gives

$$\begin{aligned}\frac{\mathcal{R}_h^{\tau\text{-IGP}}}{\mathcal{R}_h^{\text{no-IGP}}} &= 1 + \frac{\sigma}{\sigma + \gamma - 1} g + O(g^2), \\ \frac{\mathcal{R}_h^{\kappa\text{-IGP}}}{\mathcal{R}_h^{\text{no-IGP}}} &= 1 - \frac{1 - \sigma}{\sigma + \gamma - 1} g + O(g^2).\end{aligned}\tag{32}$$

Because $0 < \sigma < 1$ and $\gamma > 1$, the first ratio is greater than one and the second is less than one for all sufficiently small positive g . Moreover, $\lambda \rightarrow 0$ as $g \rightarrow 0$, so the stationary equilibrium is locally stable for sufficiently weak persistence. The same expansions therefore apply to the eventual response in (26). $\square$

The result establishes analytically that inherited preferences can accelerate structural transformation, even though they dampen the immediate response to technological change. For stronger persistence, the immediate dampening can instead dominate, as illustrated by the numerical exercise in the main text.

B.1.5. Additional Numerical Illustrations

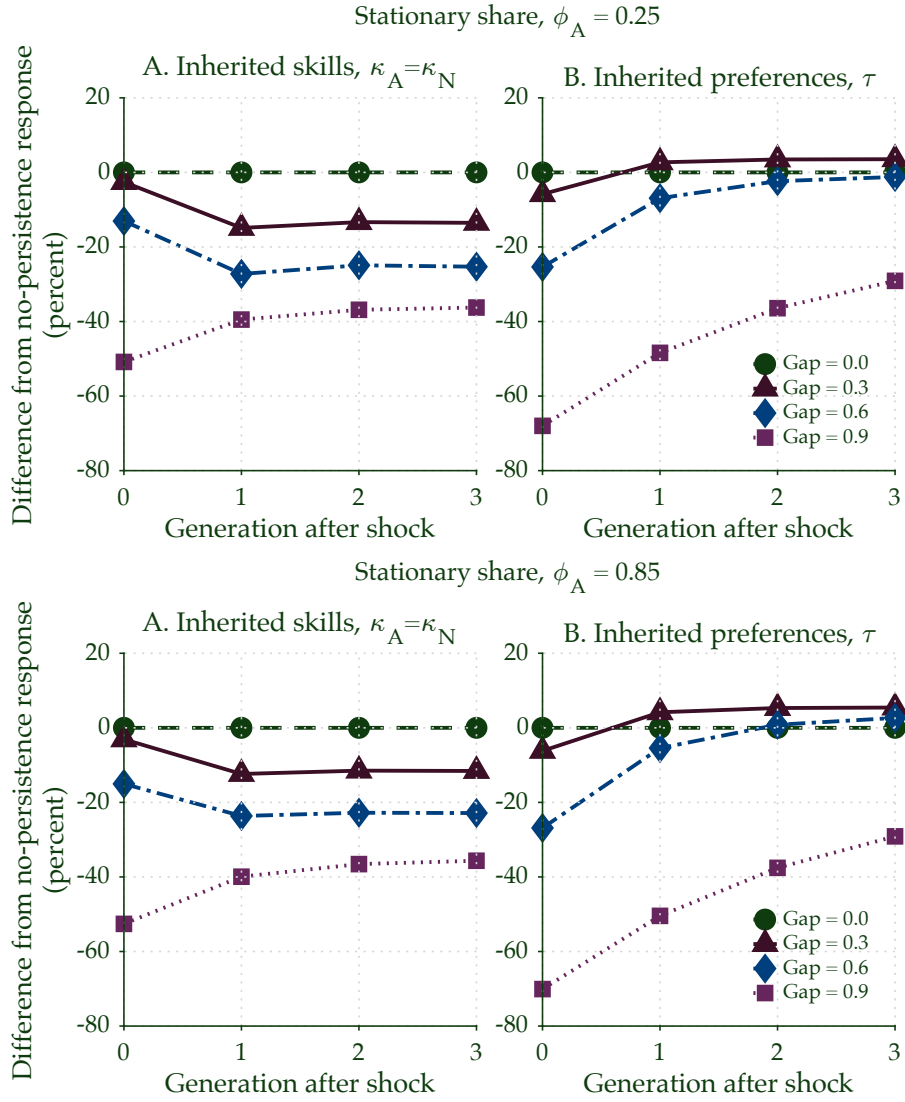


Figure 11: Numerical Responses at Alternative Stationary Agricultural Employment Shares

Note: The figure repeats the numerical exercise in Figure 3 at common stationary agricultural employment shares of $\bar{\phi}_A = 0.25$ and 0.85 , using the same permanent 0.01 -log-unit agricultural-technology shock. Within each subfigure, every economy is separately re-anchored to the stated $\bar{\phi}_A$; the legend reports the parent-sector employment gap, and Panels A and B generate that gap using symmetric inherited skills and inherited preferences, respectively. Responses equal $100 \times (\text{IGP response}/\text{no-IGP response} - 1)$, so positive values indicate faster reallocation than without IGP. All other parameters remain at the main-text benchmark: $\gamma = 2$, $\sigma = 0.3$, $\vartheta_A = \vartheta_N = 1$, and $\Omega_A = \Omega_N = 1$.

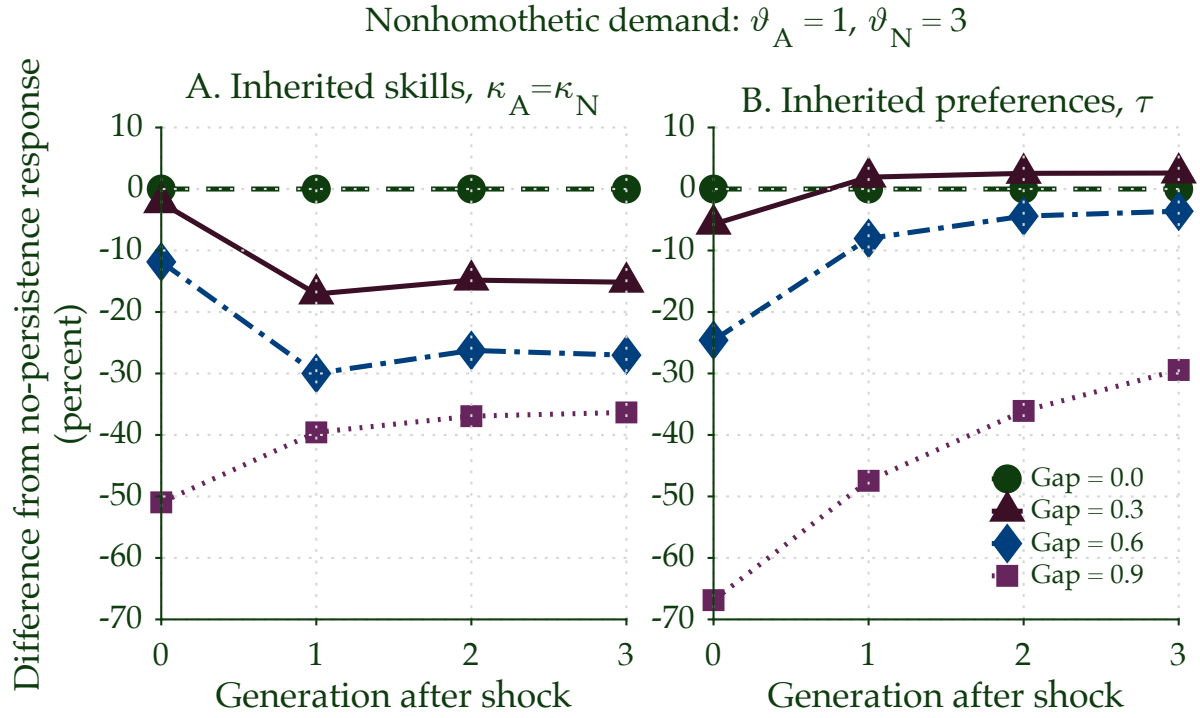


Figure 12: Numerical Responses with Nonhomothetic Demand

Note: The figure repeats the permanent 0.01-log-unit agricultural-technology shock with nonhomothetic demand, $(\vartheta_A, \vartheta_N) = (1, 3)$, rather than the homothetic benchmark in the main text. Every economy is separately re-anchored to $\bar{\phi}_A = 0.6$; the legend reports the parent-sector employment gap, and Panels A and B generate that gap using symmetric inherited skills and inherited preferences, respectively. Responses equal $100 \times (\text{IGP response/no-IGP response} - 1)$. The remaining parameters are $\gamma = 2$, $\sigma = 0.3$, and $\Omega_A = \Omega_N = 1$.

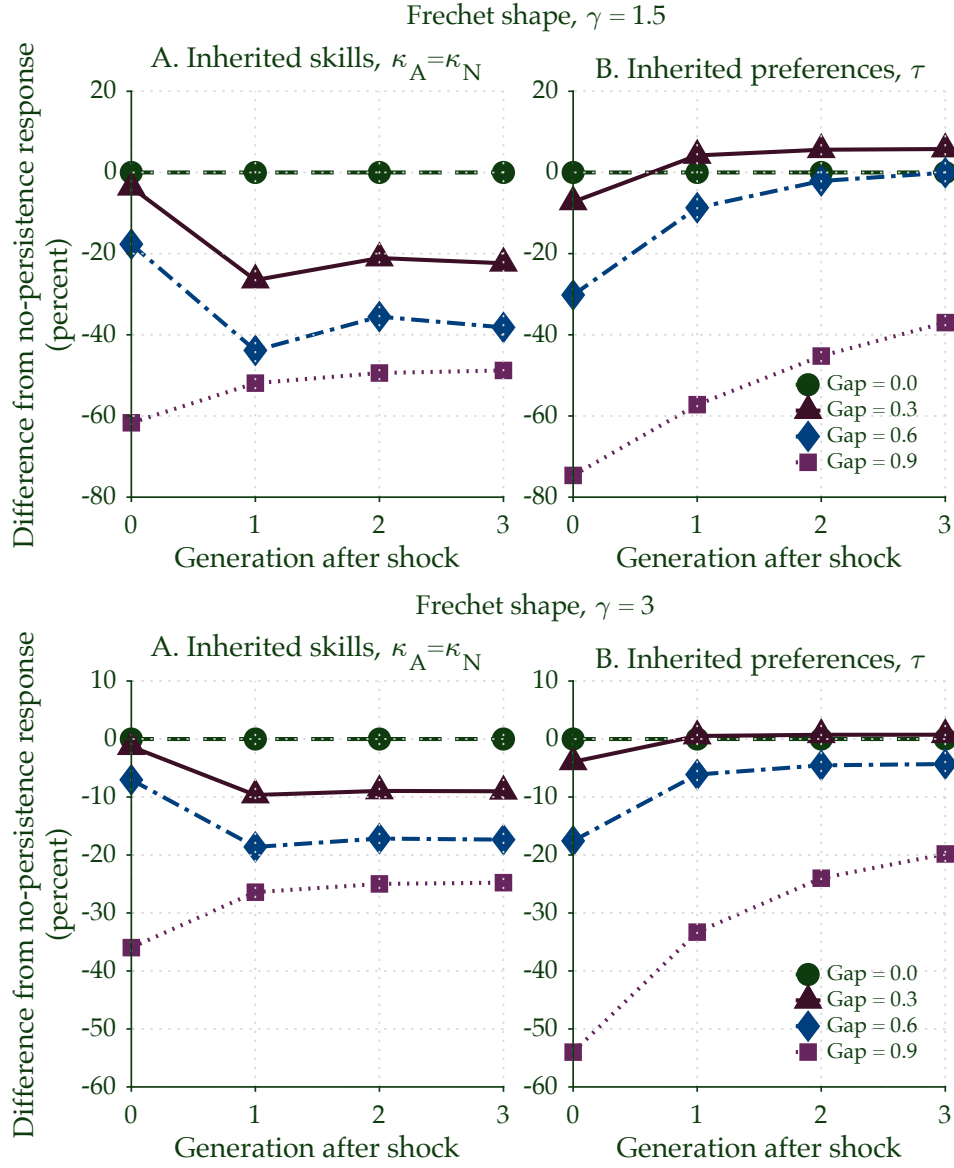


Figure 13: Numerical Responses at Alternative Fréchet Shape Parameters

Note: The figure repeats the permanent 0.01-log-unit agricultural-technology shock for $\gamma \in \{1.5, 3, 5\}$. For each γ , the inherited-skill and inherited-preference parameters are chosen separately to generate the common parent-sector employment gaps shown in the legend, and every economy is re-anchored to $\bar{\phi}_A = 0.6$. Panels A and B vary symmetric inherited skills and inherited preferences, respectively; responses are percentage differences from the corresponding no-IGP response. All other parameters remain at the benchmark: $\sigma = 0.3$, $\vartheta_A = \vartheta_N = 1$, and $\Omega_A = \Omega_N = 1$.

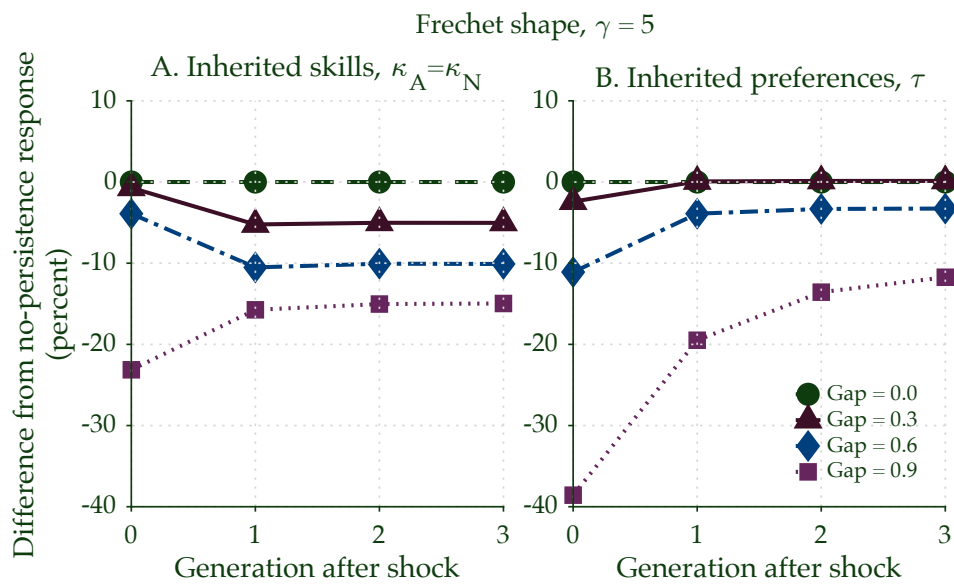


Figure 13: Numerical Responses at Alternative Fréchet Shape Parameters (continued)

Note: This panel completes Figure 13 with $\gamma = 5$; all other parameters and construction follow the preceding note.

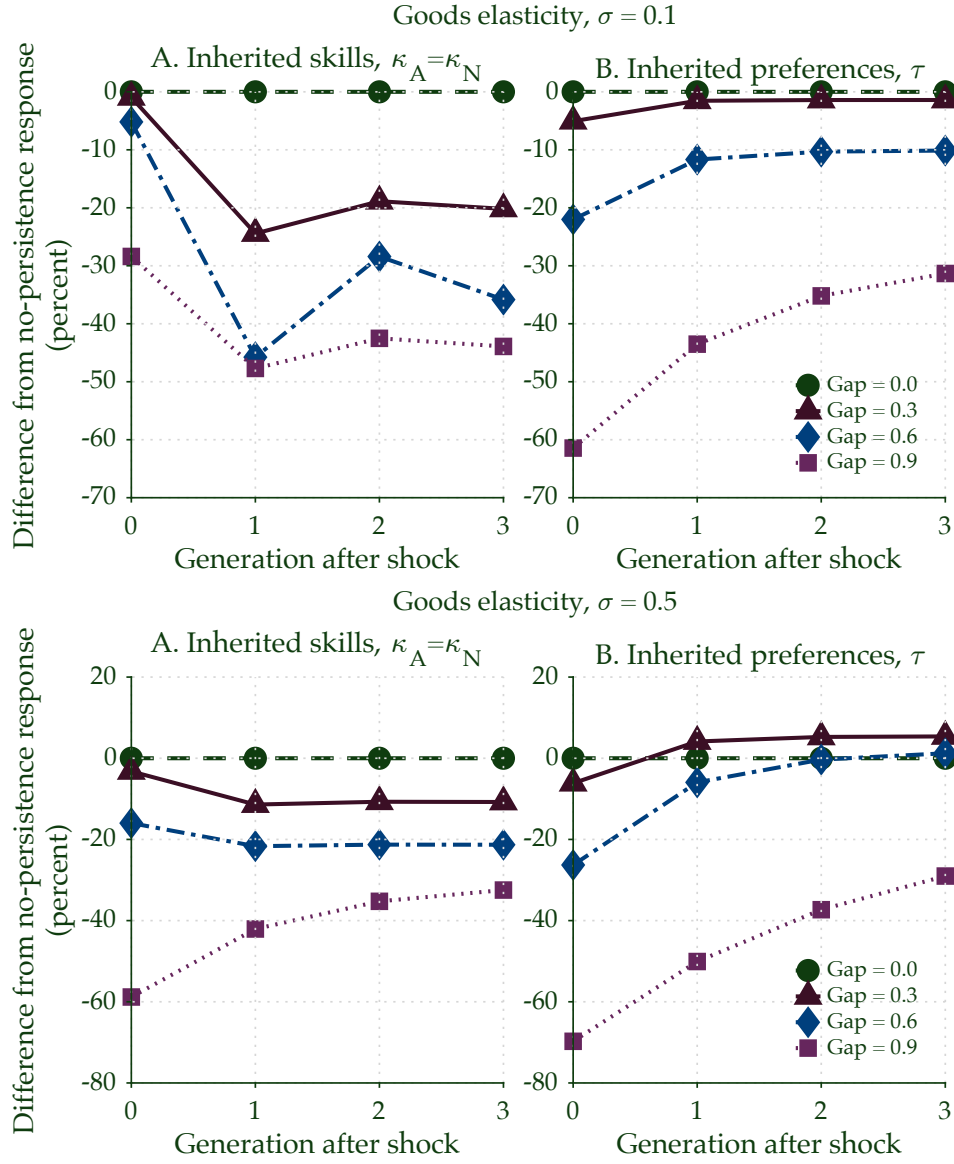


Figure 14: Numerical Responses at Alternative Elasticities of Substitution Across Goods

Note: The figure repeats the permanent 0.01-log-unit agricultural-technology shock for $\sigma \in \{0.1, 0.5, 0.9\}$. Within each subfigure, every economy is separately re-anchored to $\bar{\phi}_A = 0.6$; the legend reports the parent-sector employment gap, and Panels A and B generate that gap using symmetric inherited skills and inherited preferences, respectively. Responses are percentage differences from the corresponding no-IGP response. All other parameters remain at the benchmark: $\gamma = 2$, $\vartheta_A = \vartheta_N = 1$, and $\Omega_A = \Omega_N = 1$.

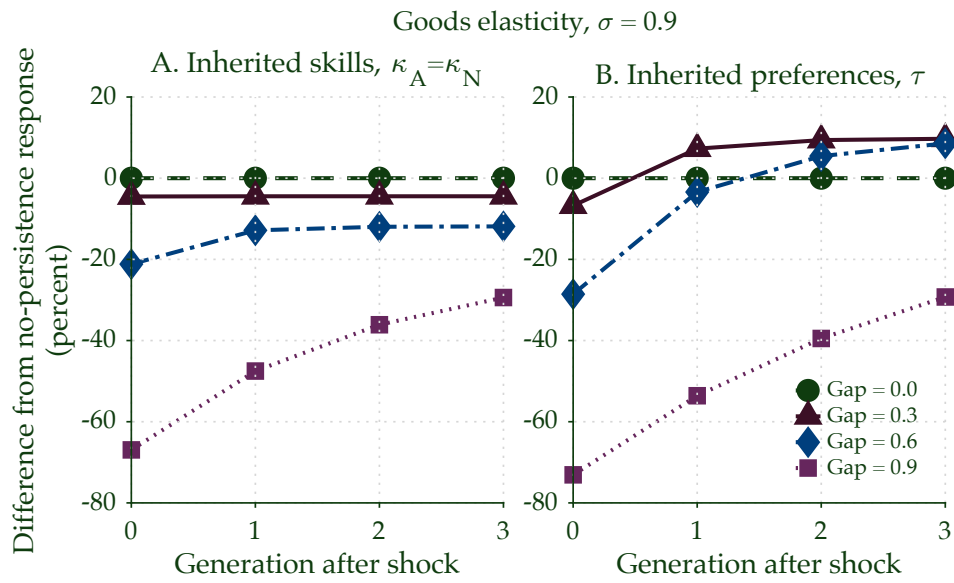


Figure 14: Numerical Responses at Alternative Elasticities of Substitution Across Goods (continued)

Note: This panel completes Figure 14 with $\sigma = 0.9$; all other parameters and construction follow the preceding note.

C. Appendix: Identification

C.1. Identification: Supporting Derivations

This appendix derives the identifying relationships for the labor supply parameters and the exogenous drivers of structural transformation established in Section 3. The results concern population moments implied by the model, rather than the estimation of those moments from the historical data.

C.1.1. Labor Supply Parameters

Conditional Log-Earnings Variance Fix a parental sector k and consider the indirect utilities of a type- k worker in each sector. Because the sector-specific skill draws are independent and satisfy $\epsilon_{i,j,t}^{-\gamma} \sim \text{Exp}(1)$, the workers' indirect utilities imply

$$\begin{aligned} V_{i,A,t}(k)^{-\gamma} &\sim \text{Exp} \left([B_{A,t} w_{A,t} \kappa_A^{\mathbb{1}(k=A)}]^\gamma \right), \\ V_{i,N,t}(k)^{-\gamma} &\sim \text{Exp} \left([B_{N,t} w_{N,t} \kappa_N^{\mathbb{1}(k=N)} (1 - \tau)^{\mathbb{1}(k=A)}]^\gamma \right). \end{aligned}$$

The exponential variables are independent because the skill draws are independent. Maximizing indirect utility is equivalent to minimizing its negative γ -th power. For independent exponential random variables, the minimum is independent of which variable attains it and is exponentially distributed with a rate equal to the sum of the individual rates. Therefore, the maximum indirect utility, $V_{i,t}^{\max}(k) \equiv \max_{j \in \{A,N\}} V_{i,j,t}(k)$, is Fréchet distributed with shape parameter γ and is independent of the sector chosen by the worker. Since the variance of a standard Gumbel random variable is $\pi^2/6$, it follows that

$$\text{Var} [\log V_{i,t}^{\max}(k) \mid s_{i,t} = j, k] = \frac{\pi^2}{6\gamma^2}.$$

For a worker who chooses sector j , earnings differ from maximum indirect utility only by the nonpecuniary benefits associated with that sector:

$$\log y_{i,j,t}(k) = \log V_{i,t}^{\max}(k) - \log B_{j,t} - \mathbb{1}(j = N, k = A) \log(1 - \tau).$$

Conditional on destination and parental sector, the final two terms are constants and do not affect the variance of log earnings. Consequently,

$$\text{Var} [\log y_{i,j,t}(k) \mid s_{i,t} = j, k] = \frac{\pi^2}{6\gamma^2},$$

which identifies γ according to equation (ID-1).

Inherited Skills and Preferences The same independence between maximum indirect utility and sector choice delivers the conditional average effective labor supplied by each parental group. The conditional mean of maximum indirect utility equals $\bar{\gamma}$ times its Fréchet scale, while each group-specific choice probability equals the corresponding sectoral scale raised to γ divided by the sum across sectors. In particular, the expected skill of a type- k worker who selects sector j is $\bar{\gamma}\phi_{j,t}(k)^{-1/\gamma}$, where $\bar{\gamma} = \Gamma(1 - 1/\gamma)$. Multiplying this conditional mean by the inherited skill advantage and the sectoral wage gives

$$y_{j,t}(k) = w_{j,t} \cdot \bar{\gamma} \cdot \kappa_j^{\mathbb{1}(k=j)} \cdot \phi_{j,t}(k)^{-1/\gamma}.$$

Under the maintained assumption that both parental groups face the same wage per efficiency unit within each sector, their earnings ratios therefore satisfy

$$\frac{y_{A,t}(A)}{y_{A,t}(N)} = \kappa_A \left(\frac{\phi_{A,t}(A)}{\phi_{A,t}(N)} \right)^{-1/\gamma}, \quad \frac{y_{N,t}(N)}{y_{N,t}(A)} = \kappa_N \left(\frac{\phi_{N,t}(N)}{\phi_{N,t}(A)} \right)^{-1/\gamma}.$$

Rearranging these expressions gives the identifying equations (ID-2) and (ID-3) for inherited skills.

To identify inherited preferences, equation (1) implies that the odds of agricultural employment within each parental group satisfy

$$\frac{\phi_{A,t}(A)}{\phi_{N,t}(A)} = \left(\frac{B_{A,t}w_{A,t}\kappa_A}{B_{N,t}w_{N,t}(1-\tau)} \right)^\gamma, \quad \frac{\phi_{A,t}(N)}{\phi_{N,t}(N)} = \left(\frac{B_{A,t}w_{A,t}}{B_{N,t}w_{N,t}\kappa_N} \right)^\gamma.$$

Taking the ratio eliminates both relative wages and common nonpecuniary benefits:

$$\mathcal{O} = \frac{\phi_{A,t}(A)/\phi_{N,t}(A)}{\phi_{A,t}(N)/\phi_{N,t}(N)} = \left(\frac{\kappa_A\kappa_N}{1-\tau} \right)^\gamma.$$

Solving for τ yields equation (ID-4). Thus, the variance of log earnings, the two within-sector earnings ratios, and the intergenerational sector-choice odds ratio identify the four

labor supply parameters from population moments under the maintained model assumptions.

C.1.2. Exogenous Drivers of Structural Transformation

I now derive the period-by-period identification of $Z_{A,t}$, $Z_{N,t}$, and $B_{N,t}/B_{A,t}$ from $\phi_{A,t}$, p_t , and Q_t . The model parameters and the previous generation's agricultural employment share, $\phi_{A,t-1}$, are taken as given, and all observed employment shares and prices are assumed to be interior and strictly positive, respectively.

First, the identified labor supply parameters determine the intergenerational sector-choice odds ratio $\mathcal{O} = (\kappa_A \kappa_N / (1 - \tau))^\gamma$. Rearranging the definition of this odds ratio gives

$$\phi_{A,t}(A) = \frac{\mathcal{O} \phi_{A,t}(N)}{1 + (\mathcal{O} - 1) \phi_{A,t}(N)}.$$

Substituting this expression into the aggregate employment equation (3) yields

$$\phi_{A,t} = \phi_{A,t-1} \frac{\mathcal{O} \phi_{A,t}(N)}{1 + (\mathcal{O} - 1) \phi_{A,t}(N)} + (1 - \phi_{A,t-1}) \phi_{A,t}(N). \quad (33)$$

The right-hand side is continuous and strictly increasing in $\phi_{A,t}(N)$, ranging from zero to one as $\phi_{A,t}(N)$ varies from zero to one. Thus, each observed $\phi_{A,t} \in (0, 1)$ uniquely determines $\phi_{A,t}(N)$ and, through the odds ratio, $\phi_{A,t}(A)$. The remaining group-specific sector choices follow from $\phi_{N,t}(k) = 1 - \phi_{A,t}(k)$. Given these shares and the inherited composition, equations (2) and (4) uniquely determine the positive effective labor supplies $H_{A,t}$ and $H_{N,t}$.

Second, goods-market clearing and sectoral production imply $X_{j,t} = Z_{j,t} H_{j,t}$. Since $\omega_{A,t}/\omega_{N,t} = X_{A,t}/(p_t X_{N,t})$, substituting the production functions into equation (9) gives

$$\frac{Z_{A,t} H_{A,t}}{Z_{N,t} H_{N,t}} = \frac{\Omega_A}{\Omega_N} \cdot p_t^\sigma \cdot Q_t^{(\vartheta_A - \vartheta_N)(1-\sigma)}.$$

Rearranging identifies $Z_{N,t}/Z_{A,t}$ according to equation (ID-5).

Third, the relative expenditure-share equation also implies the following relative quantity demand:

$$\frac{X_{A,t}}{X_{N,t}} = \frac{\Omega_A}{\Omega_N} \cdot p_t^\sigma \cdot Q_t^{(\vartheta_A - \vartheta_N)(1-\sigma)}.$$

Substituting this relationship into the nonhomothetic CES aggregator (8) and rearranging

gives agricultural consumption as

$$X_{A,t} = \Omega_A Q_t^{\vartheta_A} \left[\Omega_A + \Omega_N \left(p_t Q_t^{\vartheta_N - \vartheta_A} \right)^{1-\sigma} \right]^{\frac{\sigma}{1-\sigma}}.$$

Because $X_{A,t} = Z_{A,t} H_{A,t}$ and $H_{A,t} > 0$, dividing by agricultural effective labor identifies the level of agricultural technology in equation (ID-6). The level of nonagricultural technology is then uniquely determined from the identified relative technology, $Z_{N,t} = (Z_{N,t}/Z_{A,t}) Z_{A,t}$.

Finally, the sector-choice equation for nonag-born workers implies

$$\frac{\phi_{N,t}(N)}{\phi_{A,t}(N)} = \left[\kappa_N \frac{B_{N,t}}{B_{A,t}} \frac{w_{N,t}}{w_{A,t}} \right]^{\gamma}.$$

The competitive wage condition (7) implies $w_{N,t}/w_{A,t} = p_t Z_{N,t}/Z_{A,t}$. Substituting this wage ratio and solving for $B_{N,t}/B_{A,t}$ yields equation (ID-7).

Each step is unique and returns strictly positive sectoral technologies and relative nonpecuniary benefits. The recovered fundamentals satisfy the sector-choice equations, sectoral production, consumer demand, and goods-market clearing by construction. Therefore, the observed aggregate employment share, relative goods price, and real consumption uniquely identify the three exogenous fundamentals conditional on the model parameters and inherited worker composition.

D. Appendix: Quantitative Application

D.1. Quantitative Implementation and Additional Results

This appendix documents the data, consumer-demand calibration, model inversion, counterfactual construction, and channel decomposition used in the quantitative analysis.

Data and timing. The quantitative exercise covers 1880, 1900, 1920, and 1940. The period- t cohort consists of ag-born and nonag-born workers with shares $\phi_{A,t-1}$ and $1 - \phi_{A,t-1}$, respectively. Thus the agricultural employment share in 1860, $\phi_{A,0} = 0.665393$, determines cohort composition in 1880; thereafter, the observed aggregate share in one census determines the composition used for the next census. Table 18 describes the inputs and their sources. Aggregate and subgroup employment shares are constructed from the

linked censuses as described in Section 1. Agricultural output shares, relative prices, and real GDP per capita are from [Dennis and İřcan \(2009\)](#), [Alvarez-Cuadrado and Poschke \(2011\)](#), and [Maddison \(1995\)](#), respectively. I normalize the latter two series to one in 1880.

Table 18: Data Used in the Quantitative Analysis

Variable	Description and use	Source or construction
$\phi_{A,0}$	Initial share of ag-born workers entering in 1880; determines initial cohort composition.	1860 agricultural employment share in the linked census sample.
$\phi_{A,t}$	Aggregate agricultural employment share; targeted by the inversion and used as the next period's ag-born share.	Linked census sample, 1880–1940.
$\phi_{A,t}(A),$ $\phi_{A,t}(N)$	Agricultural employment shares of ag-born and nonag-born workers; untargeted validation moments.	Linked census sample, 1880–1940.
$\omega_{A,t}$	Agricultural output share; calibrates and evaluates the consumer-demand parameters.	Dennis and İřcan (2009) .
$p_t =$ $p_{N,t}/p_{A,t}$	Price of nonagricultural relative to agricultural goods; targeted by the inversion.	Alvarez-Cuadrado and Poschke (2011) ; indexed to one in 1880.
$Q_t = Y_t/P_t$	Real GDP per capita; targeted by the inversion.	Maddison (1995) ; indexed to one in 1880.

Note: Employment measures use the sample and sector definitions described in Section 1.

Consumer-demand calibration. I set $\sigma = 0.3$, normalize $\Omega_N = 1$ and $\vartheta_A = 1$, and choose

$$\Omega_A = \frac{\omega_{A,1880}}{1 - \omega_{A,1880}} = 0.449275$$

so that the model exactly matches the 1880 agricultural output share. For any $\vartheta_N > 1$, the implied share is

$$\hat{\omega}_{A,t}(\vartheta_N) = \frac{R_t(\vartheta_N)}{1 + R_t(\vartheta_N)}, \quad R_t(\vartheta_N) = \Omega_A p_t^{\sigma-1} Q_t^{(1-\vartheta_N)(1-\sigma)},$$

where $p_t = p_{N,t}/p_{A,t}$ and $Q_t = Y_t/P_t$. I estimate

$$\hat{\vartheta}_N = \arg \min_{\vartheta_N > 1} \sum_{t \in \{1900, 1920, 1940\}} [\omega_{A,t} - \hat{\omega}_{A,t}(\vartheta_N)]^2,$$

obtaining $\hat{\vartheta}_N = 4.630$. The optimization uses the transformation $\vartheta_N = 1 + \exp(u)$ and multiple starting values; the reported fit is the solution with the smallest sum of squared residuals.

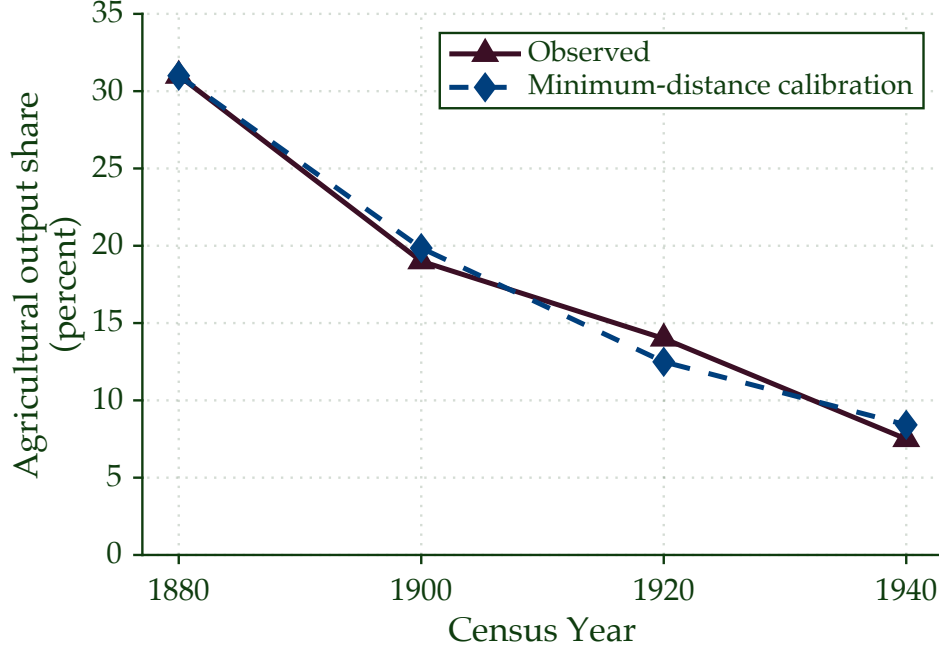


Figure 15: Consumer Demand Calibration of the Agricultural Output Share

Note: The figure compares the observed agricultural output share with the baseline minimum-distance calibration of consumer demand. The baseline fixes $\sigma = 0.3$ and $\vartheta_A = 1$, estimates $\vartheta_N = 4.630$ from the 1900–1940 shares, normalizes $\Omega_N = 1$, and chooses Ω_A to match the 1880 share. Output shares, relative prices, and real GDP per capita are from [Dennis and İřcan \(2009\)](#), [Alvarez-Cuadrado and Poschke \(2011\)](#), and [Maddison \(1995\)](#), respectively.

Period-by-period model inversion. Appendix [C.1.2](#) provides the formal derivation and proof of the unique mapping from $(\phi_{A,t}, p_t, Q_t)$ to $(Z_{A,t}, Z_{N,t}, B_{N,t}/B_{A,t})$ established in Proposition 5. The quantitative implementation evaluates those identifying equations period by period under the calibrated parameters and timing described above.

Recursive implementation and model fit. Starting from the observed or imposed initial condition $\phi_{A,0}$, I apply the inversion sequentially because the recovered allocation in period t supplies the inherited composition $\phi_{A,t}$ used in period $t + 1$. In the historical inversion, I use the observed $\phi_{A,t}$, rather than its fitted value, as the next period’s inherited composition. At every date, the numerical implementation reconstructs the three targeted outcomes and the CES aggregator with absolute errors below 10^{-8} . The agricultural output share is not an additional identifying moment in this inversion. Once p_t and

Q_t are imposed, equation (9) determines the agricultural output share from the calibrated consumer-demand parameters. The discrepancy from the observed output share therefore remains the consumer-demand calibration residual rather than a fourth equation in the period-by-period inversion.

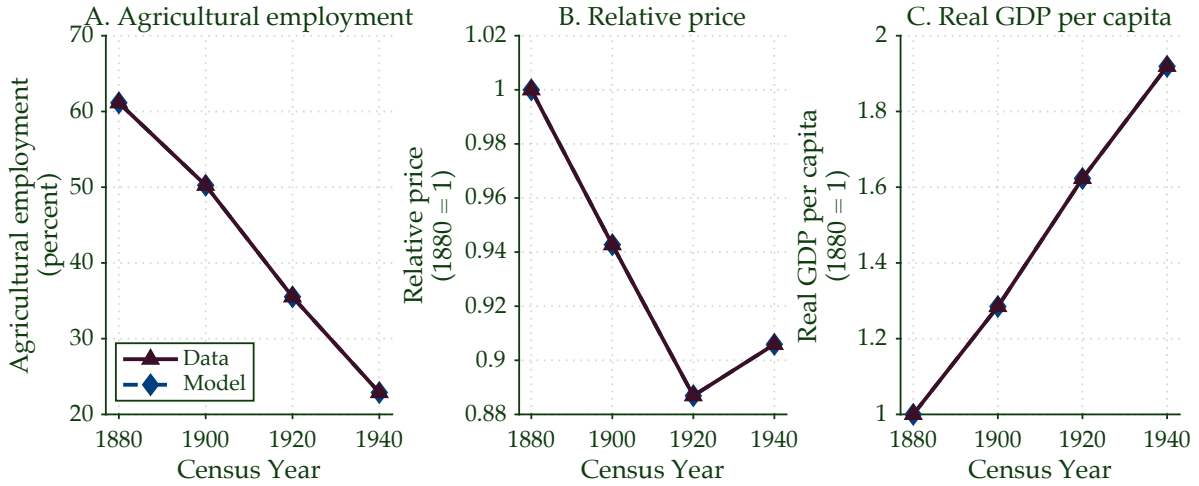


Figure 16: Targeted Moments for Model Inversion

Note: The figure compares the data with the outcomes reproduced by the period-by-period model inversion. Agricultural employment is reported in percent; the relative price, p_N/p_A , and real GDP per capita are indexed to one in 1880. The inversion targets all three series exactly in 1880, 1900, 1920, and 1940, recursively using the previous period's agricultural employment share as the current share of ag-born workers. Employment shares are calculated from the linked censuses; relative prices and real GDP per capita are from [Alvarez-Cuadrado and Poschke \(2011\)](#) and [Maddison \(1995\)](#), respectively.

Untargeted Subgroup Shares. The inversion also implies $\phi_{A,t}(A)$ and $\phi_{A,t}(N)$, but does not target their observed counterparts. Conditional on $\phi_{A,t-1}$ and the time-invariant labor-supply parameters, the single aggregate target $\phi_{A,t}$ identifies the subgroup choices through equation (33), which in turn fixes both subgroup shares. Their comparison with the data in Figure 17 is therefore an overidentifying check. The inherited-skill and inherited-preference parameters are estimated from 1940 income and sector-choice data, so the model does not reproduce the substantially greater subgroup persistence observed in 1880. Matching these subgroup paths would require time-varying persistence parameters or an additional model mechanism.

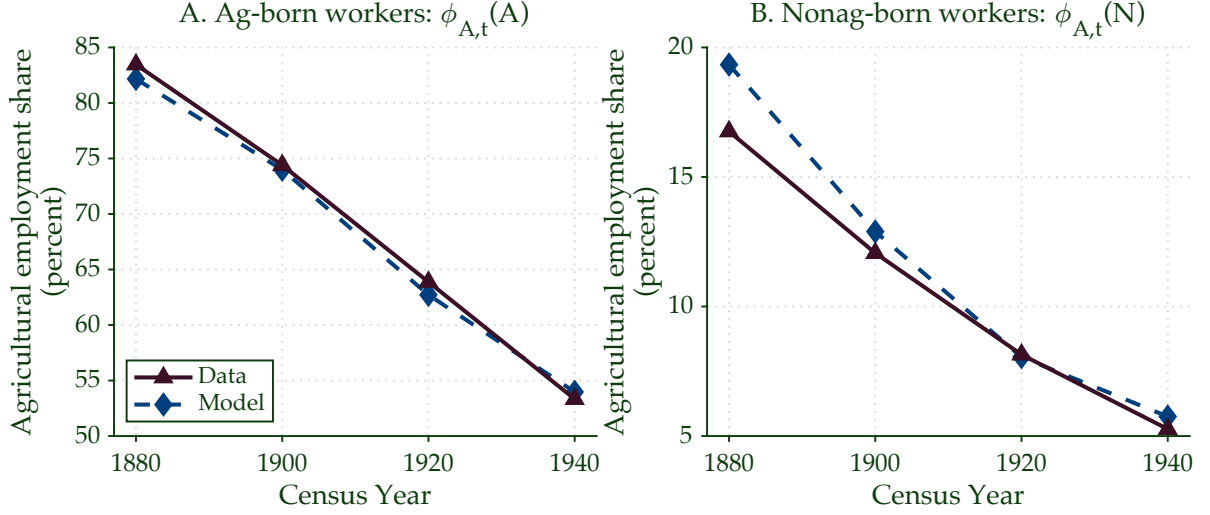


Figure 17: Agricultural Employment Share for Ag-born and Nonag-born Workers

Note: The figure compares observed and model-implied agricultural employment shares for ag-born and nonag-born workers in the linked censuses. These subgroup shares are not targeted: the inversion matches only the aggregate employment share, relative price, and real GDP per capita in each year, using the time-invariant baseline labor-supply parameters estimated from 1940.

Constructing the counterfactuals. Let superscript b denote the benchmark inversion and define the benchmark growth factors

$$g_t^A = \frac{Z_{A,t}^b}{Z_{A,1880}^b}, \quad g_t^N = \frac{Z_{N,t}^b}{Z_{N,1880}^b}, \quad g_t^B = \frac{(B_N/B_A)_t^b}{(B_N/B_A)_{1880}^b}.$$

I consider the benchmark and three counterfactuals: no inherited skills ($\kappa_A = \kappa_N = 1$), no inherited preferences ($\tau = 0$), and no intergenerational persistence ($\kappa_A = \kappa_N = 1, \tau = 0$). For each specification r , I first apply the inversion under the corresponding parameters to the common 1880 targets. This produces specification-specific anchors $Z_{A,1880}^r$, $Z_{N,1880}^r$, and $(B_N/B_A)_{1880}^r$. The subsequent fundamentals are

$$Z_{A,t}^r = Z_{A,1880}^r g_t^A, \quad Z_{N,t}^r = Z_{N,1880}^r g_t^N, \quad (B_N/B_A)_t^r = (B_N/B_A)_{1880}^r g_t^B.$$

I then solve the equilibrium forward, using the simulated $\phi_{A,t}^r$ as the parental composition of the next cohort. This construction makes all four specifications match the 1880 agricultural employment share, relative price, and real GDP per capita, while exposing them to the same proportional growth in fundamentals thereafter. Worker reallocation is $100(\phi_{A,1880}^r - \phi_{A,1940}^r)$ percentage points.

Inferred Drivers Without Inherited Skills or Inherited Preferences Figure 18 separates the effect of omitting inherited skills from the effect of omitting inherited preferences in the baseline inversion. The comparison uses the baseline values of $(\kappa_A, \kappa_N, \tau)$ whenever a persistence channel remains active and changes no other parameter.

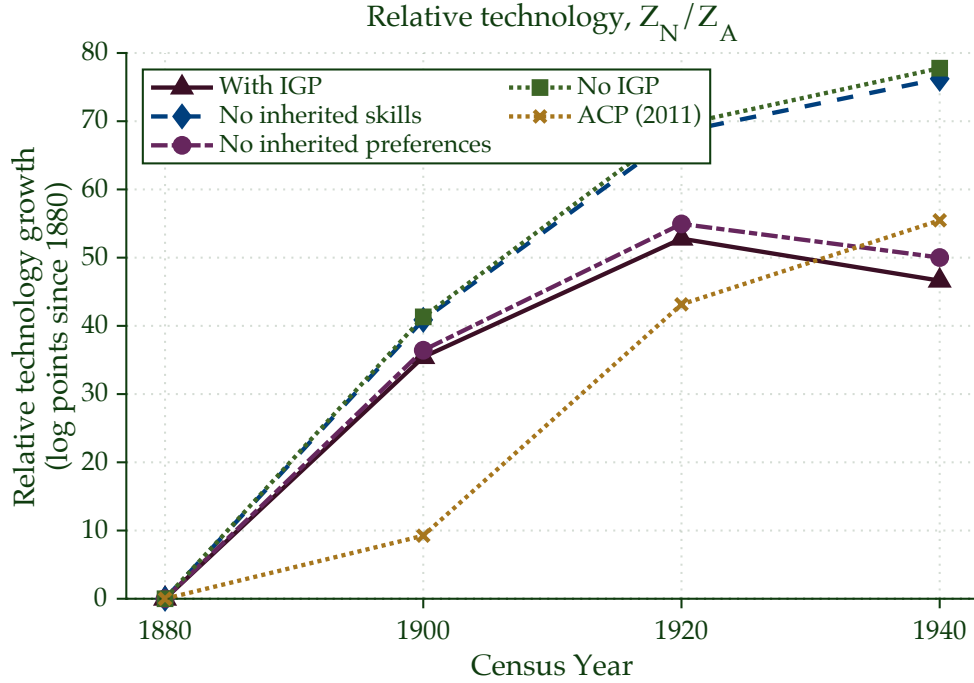


Figure 18: Inferred Relative Technology under Alternative IGP Restrictions

Note: The figure plots the cumulative log change in $Z_{N,t}/Z_{A,t}$ under the baseline inherited-skill and inherited-preference estimates, after setting only $\kappa_A = \kappa_N = 1$, after setting only $\tau = 0$, and after imposing both restrictions. The remaining parameters, γ , and all consumer-demand parameters stay at their baseline values in each inversion. Every inversion matches the same agricultural employment share, relative price, and real GDP per capita in each year. The Alvarez-Cuadrado-Poschke series is the same nonfarm-to-farm relative TFP benchmark shown in Figure 6.

Under the baseline calibration, removing inherited skills raises the log change in relative technology from 46.6 to 76.2 points over 1880–1940. Removing inherited preferences instead raises it to 50.0 points, while removing both sources raises it to 77.8 points. Thus the faster relative-technology growth inferred when IGP is omitted is driven primarily by inherited skills.

Interval-level Shapley decomposition. For specification r and an interval ending in t , let F_0^r and F_1^r denote the beginning- and end-of-interval fundamentals, and let M_0^r and M_1^r denote the corresponding inherited parental compositions. Write

$$y_{ab}^r = \phi_A(F_a^r, M_b^r), \quad a, b \in \{0, 1\}.$$

The two-player Shapley contributions to the decline in the agricultural employment share are

$$C_t^r = \frac{1}{2} [(y_{00}^r - y_{10}^r) + (y_{01}^r - y_{11}^r)],$$

$$P_t^r = \frac{1}{2} [(y_{00}^r - y_{01}^r) + (y_{10}^r - y_{11}^r)],$$

where C_t^r is the immediate effect of technologies and the relative payoff shifter and P_t^r is the dynamic effect transmitted through parental composition. The averages span the two possible orders in which the inputs change. They satisfy

$$C_t^r + P_t^r = y_{00}^r - y_{11}^r$$

in every interval. I sum each channel over 1880–1900, 1900–1920, and 1920–1940, then report its counterfactual-minus-benchmark difference in percentage points:

$$100 \sum_t (C_t^r - C_t^b), \quad 100 \sum_t (P_t^r - P_t^b).$$

Their sum equals the difference between counterfactual and benchmark worker reallocation reported in Table 4.

D.1.1. Robustness to Alternative Calibrations

I assess the robustness of the quantitative results to alternative consumer-demand and labor-supply calibrations. Each robustness exercise repeats the entire procedure: re-invert the historical fundamentals under the alternative parameters, re-anchor every counterfactual to the common 1880 targets, simulate forward using that specification's inferred growth factors, and recompute the interval-level Shapley decomposition. The CLM exercise changes only the consumer-demand parameters to $(\sigma, \vartheta_A, \vartheta_N) = (0.33, 1, 1/0.33)$. The location labor-supply exercise retains the baseline consumer-demand parameters and uses

$$(\gamma, \kappa_A, \kappa_N, \tau) = (2.319, 1.306, 1.422, 0.284).$$

The topcode-adjusted exercise likewise retains the baseline consumer-demand parameters and uses

$$(\gamma, \kappa_A, \kappa_N, \tau) = (2.180, 1.508, 1.740, 0.324).$$

Thus the robustness results incorporate both the direct effect of alternative parameters and the associated changes in the inferred historical fundamentals; they do not hold the benchmark fundamental paths fixed in levels or growth rates.

Table 19: Robustness of Immediate, Dynamic, and Cumulative Effects

Counterfactual	Immediate effect	Dynamic effect	Cumulative effect
Percentage points			
<i>Panel A: CLM consumer-demand calibration</i>			
No inherited skills	2.48	3.01	5.49
No inherited preferences	3.13	−2.33	0.81
No intergenerational persistence	3.57	1.48	5.05
<i>Panel B: Location labor-supply calibration</i>			
No inherited skills	1.17	2.29	3.46
No inherited preferences	2.16	−1.66	0.49
No intergenerational persistence	2.00	1.08	3.08
<i>Panel C: Topcode-adjusted labor-supply calibration</i>			
No inherited skills	2.43	2.96	5.38
No inherited preferences	3.10	−2.29	0.81
No intergenerational persistence	3.50	1.46	4.96

Note: Each panel repeats the interval-level Shapley decomposition under an alternative calibration. Panel A replaces the consumer-demand parameters with the CLM mapping: $\sigma = 0.33$, $\vartheta_A = 1$, and $\vartheta_N = 1/0.33$. Panels B and C retain the baseline consumer-demand parameters and use, respectively, the location estimates $(\gamma, \kappa_A, \kappa_N, \tau) = (2.319, 1.306, 1.422, 0.284)$ and topcode-adjusted estimates $(2.180, 1.508, 1.740, 0.324)$. Each specification re-infers the historical fundamentals and re-anchors every counterfactual to the common 1880 targets; the immediate and dynamic effects sum to the cumulative effect.

Table 19 shows that the channel results are qualitatively stable across the alternative calibrations. Removing inherited skills raises reallocation through both channels, whereas removing inherited preferences produces a large immediate effect that is substantially offset by the dynamic effect.

Table 20: Relative-Technology Growth under Alternative Calibrations and Persistence Restrictions

Counterfactual	Benchmark growth	Counterfactual growth	Difference from benchmark
1880–1940 log points			
<i>Panel A: CLM consumer-demand calibration</i>			
No inherited skills	−30.04	−0.45	29.60
No inherited preferences	−30.04	−26.65	3.39
No intergenerational persistence	−30.04	1.10	31.15
<i>Panel B: Location labor-supply calibration</i>			
No inherited skills	52.25	72.46	20.21
No inherited preferences	52.25	55.06	2.81
No intergenerational persistence	52.25	73.71	21.46
<i>Panel C: Topcode-adjusted labor-supply calibration</i>			
No inherited skills	46.92	76.77	29.85
No inherited preferences	46.92	50.28	3.37
No intergenerational persistence	46.92	78.30	31.38

Note: Benchmark and counterfactual growth are the cumulative 1880–1940 log changes in $Z_{N,t}/Z_{A,t}$ under the indicated calibration. “No inherited skills” sets $\kappa_A = \kappa_N = 1$, “No inherited preferences” sets $\tau = 0$, and “No intergenerational persistence” imposes both restrictions. The final column equals counterfactual growth minus benchmark growth within the same panel. The three panels use the same alternative consumer-demand and labor-supply calibrations as Table 19, and every row re-inverts the same observed employment, relative-price, and real-output paths.

Across these conventional calibration checks, removing all IGP raises inferred relative-technology growth by 21.5 to 31.4 log points relative to the corresponding full-IGP inversion.

I also assess whether the counterfactual results are sensitive to the skill distribution used to estimate inherited skills and inherited preferences. For this exercise, I retain the baseline Fréchet model’s γ and every baseline consumer-demand parameter, but replace $(\kappa_A, \kappa_N, \tau)$ with the estimates from the bivariate lognormal and Fréchet–Frank specifications reported in Table 12. I then re-infer the historical fundamentals, re-anchor the counterfactuals to the common 1880 targets, and repeat the interval-level Shapley decomposition under each alternative parameter vector.

Table 21: Immediate and Dynamic Components under Alternative Skill Distributions

Counterfactual	Immediate effect	Dynamic effect	Cumulative effect
Percentage points			
<i>Panel A: Bivariate lognormal estimates</i>			
No inherited skills	1.04	1.12	2.16
No inherited preferences	3.90	−2.97	0.93
No intergenerational persistence	3.64	−1.50	2.13
<i>Panel B: Fréchet–Frank estimates</i>			
No inherited skills	3.77	3.57	7.34
No inherited preferences	2.75	−2.25	0.50
No intergenerational persistence	4.50	2.45	6.95

Note: Each panel replaces only $(\kappa_A, \kappa_N, \tau)$ with the estimates implied by the indicated skill distribution and retains the baseline γ and consumer-demand parameters. The historical fundamentals are re-inferred under each parameter vector, and every counterfactual is re-anchored to the common 1880 targets. The immediate and dynamic effects sum to the cumulative effect, which is the change in 1880–1940 worker reallocation relative to the full-IGP benchmark under the same parameter vector.

Table 21 therefore isolates sensitivity to the way alternative skill distributions map the common targeted moments into inherited-skill and inherited-preference estimates rather than sensitivity to the rest of the macroeconomic model.

Table 22: Relative-Technology Growth under Alternative Distributional Estimates

Counterfactual	Benchmark growth	Counterfactual growth	Difference from benchmark
1880–1940 log points			
<i>Panel A: Bivariate lognormal estimates</i>			
No inherited skills	61.42	73.04	11.62
No inherited preferences	61.42	67.73	6.31
No intergenerational persistence	61.42	77.77	16.36
<i>Panel B: Fréchet–Frank estimates</i>			
No inherited skills	38.73	76.91	38.18
No inherited preferences	38.73	40.63	1.90
No intergenerational persistence	38.73	77.77	39.05

Note: Benchmark and counterfactual growth are the cumulative 1880–1940 log changes in $Z_{N,t}/Z_{A,t}$ under the indicated distributional parameter estimates. “No inherited skills” sets $\kappa_A = \kappa_N = 1$, “No inherited preferences” sets $\tau = 0$, and “No intergenerational persistence” imposes both restrictions. The final column equals counterfactual growth minus benchmark growth within the same panel. The panels replace only $(\kappa_A, \kappa_N, \tau)$ with the bivariate-lognormal or Fréchet–Frank estimates, retain the baseline γ and consumer-demand parameters, and re-invert the same observed paths in every row.

The no-IGP increase is 16.4 log points under the bivariate-lognormal estimates and 39.1 log points under the Fréchet–Frank estimates, with inherited skills again accounting for most of the difference in both cases.