Teacher Labor Market and the Dynamics of Inequality: An Analytical Framework

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Preliminary

Abstract

Teachers are a key input for the production of student achievement. This paper studies a new feedback mechanism between teacher quality and economy-wide human capital distribution in a dynamic environment where (1) human capital dispersion amplifies the selection effects on teacher quality, and (2) teacher quality affects the dispersion itself through endogenous human capital formation. I use evidence on how duty-to-bargain laws affect the teacher labor market and children's outcomes to identify the model in closed form. Counterfactual results suggest that policies that raise the returns to human capital among teachers, such as performance-based compensations, have large dynamic spillover effects such as reducing income inequality among non-teachers and boosting intergenerational mobility. The teacher labor market also propagates the effects of skill-biased technical changes, leading to greater increases in long-run inequality.

JEL classification: I24, J24, J31, J45

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1. Introduction

Teachers play a fundamental role in shaping students' achievements and path to upward mobility (Rivkin et al. 2005, Chetty et al. 2014b, Card et al. 2022). As a result, education policies that attract the best talent into the teaching profession have profound implications not only on the structure of teacher labor market but also on the human capital of the next generation (Hanushek 2011).

While recent researches have made significant progress towards measuring the impacts of education policies on the teacher labor market and student outcomes (Biasi et al. 2021, Lovenheim and Willén 2019, Tincani 2021, Card et al. 2022), two important questions remain to be answered. First, because teacher selection shapes the human capital distribution in the future, how does it affect inequality dynamics in non-teacher labor markets and the propagation of aggregate shocks such as the skill-biased technical changes? Second, how does the above-mentioned effects evolve over time as the children being affected grow up, join the labor market, and (some of which) become teachers themselves? Will the estimates in the current literature be a lower or upper bound in a dynamic environment? These questions are important for analyzing the long-run general equilibrium impacts of education policies as well as understanding the unique role of teacher labor market in the aggregate economy.

In this paper, I study these two questions in an overlapping-generations model of human capital formation à la Benabou (2002) and consider occupation selection into teaching and non-teaching professions. The key insight of the model is that the selection effects of education policies studied in the literature depend on the dispersion of human capital in the population to begin with. Therefore, in an environment with human capital formation so that the degree of dispersion is endogenous, changes in teacher selection have large *dynamic* effects.

The mechanism is described as follows: consider a scenario where decreasing rewards to human capital in the teaching profession pushes the most talented individuals into non-teaching occupations and thus reduces teacher quality. Deteriorating teacher quality reduces human capital in the next generation, with the effects being disproportionately larger among low-income families when teacher quality and parental investments are substitutes.[1] As a result, the economy has lower intergenerational mobility and a greater dispersion of human capital to begin with in the next generation. Importantly, this increased human capital dispersion reinforces the selection channel and leads to further reductions in teacher quality - a vicious cycle.

To quantify the mechanism, I show that with parametric assumptions, the model provides analytical characterizations of optimal individual decisions as well as the transition path of the equilibrium human capital distribution. I also prove that the key parameters, especially the ones governing the human capital production function, are identified in closed form using cross-sectional moments and estimates on how teacher pay rigidities affects teacher labor market and children's outcomes. I utilize variations in duty-to-bargain laws across states and over time to measure the effects of teacher pay compression on teacher labor markets. In particular, I find that the enactment of such laws reduce both employment and earnings dispersion among teachers, while having mildly negative effects on the level of average earnings. I also borrow the corresponding estimates on children's earnings from Lovenheim and Willén (2019) where the authors find that duty-to-bargain laws reduce the earnings of children affected, with the effects being larger among children with parents from disadvantaged backgrounds. As non-targeted moments, the calibrated model also predicts teacher value-added that is very close to the estimates by Chetty et al. (2014a).

In counterfactual analyses, I show that even though teachers account for less than 5% of the total workforce, they have disproportionate impacts on the dynamics of inequality in the aggregate economy due to their unique roles in human capital formation. In addition, the feedback mechanism proposed in this paper results in large amplifications of aggregate shocks along the transition path.

In the first counterfactual experiment, I raise the returns to human capital in the teaching profession by 5% to mimic a performance-based compensation reform. The magnitude of 5% is chosen to be the same as the initial impacts that duty-to-bargain

[1] See Lee and Seshadri (2019) and Yum (2023). I will also verify in this condition in the calibration results using empirical evidence from duty-to-bargain laws.

laws had on the income dispersion among teachers in the empirical findings, albeit in a different direction. I find that only two-fifth of the initial impacts on teachers' income inequality, measured in the coefficient of variations, survive in the long-run steady state. Income inequality among non-teachers, however, reduces significantly by 3%, reflecting changes in the human capital dispersion. Intergenerational elasticity of earnings also decreases from 0.36 to 0.27 in the long run. In other words, changing returns to human capital in the teaching profession pushes the economy along the Great Gatsby curve (Corak 2013) towards less inequality and more intergenerational mobility. I also show that the magnitude of these effects varies along the transition path, approaching the new steady-state in about two generations. As a result, static or one-generation analyses overstate the effects of performance-based compensation reforms on income inequality within teachers and understate the spillover effects on intergenerational mobility and the income inequality among non-teachers.

In the second counterfactual, I study the role of teacher selection in propagating aggregate shocks, in particular on how the "convexification" of non-teaching occupations (Autor et al. 2020) affect income inequalities. I find that absent changes in teacher quality, the increase in income inequality among non-teachers would be 50% smaller in the long run. This is because increasing rewards to human capital in the non-teaching profession reduces teacher quality, leading to a much larger dispersion of human capital in consecutive generations. A model-based decomposition also shows that to neutralize the effects of the skilled biased technical change (SBTC), the returns to human capital in the teaching profession needs to rise *relatively more* than that in non-teaching occupations to compensate for the fact that the SBTC also widens the gap in parental income and their investments in children's human capital formation as a separate channel from changing teacher quality.

Related Literature

This paper builds on the literature that studies the determinants of inequality and intergenerational mobility. The literature has traditionally focused on factors that affect the demand for education, such as credit constraints (Lee and Seshadri 2019, Caucutt and Lochner 2020), information frictions (Hoxby and Turner 2015), and neighborhood effects (Chetty et al. 2014b, Durlauf and Seshadri 2018, Fogli and Guerrieri 2019). This paper contributes to the literature by studying the supply side of education and show that teacher market reforms could be powerful instruments moving the economy along the Great Gatsby curve toward lower inequalities and greater intergenerational mobility.

This paper is also related to the large body of literature that studies the structure of teacher labor market and its implications on students. The most related papers are Bacolod (2007), Rothstein (2015), Lovenheim and Willén (2019), Tincani (2021), Biasi et al. (2021), and Card et al. (2022). The literature commonly finds that rewarding more effective teachers raises teacher quality and result in improved children's outcomes, especially for those with disadvantaged backgrounds. This paper contributes to the literature by incorporating these one-generation estimates into an overlapping-generations setting and uncover large dynamic spillover effects into non-teaching professions. The results highlight the unique position that the teacher labor market plays in the aggregate economy and in shaping long-run inequalities.

2. Model

I study an overlapping-generations economy populated by agents that live for two periods - children and adults. Children do not make any decisions. Their human capital is formed through a production function that takes teacher quality and parental investments as inputs. Adults with different levels of human capital supply labor inelastically and select into two occupations: teachers and workers (non-teachers). After occupation selection, adult parents choose child investments that maximizes their utility from consumption and preferences on their children's human capital.

2.1 Occupation Selection

In the beginning of each period, adults with human capital h make occupation choice after observing idiosyncratic preference shock ν that follows a Gumbel distribution with scale parameter θ. They solve the following occupation choice problem:

$$\max_{j\in\{1,2\}} \mathbb{1}_{j=1}(\underbrace{\log(wh^{\psi_1}\cdot\kappa)+\nu}_{\text{teachers}}) + \mathbb{1}_{j=2}\underbrace{\log(h^{\psi_2})}_{\text{workers}}$$

where w is the relative wage across occupations, κ captures the systematic cost or taste for becoming teachers, and ψ_j is the occupation-specific returns to human capital.

Assume that the underlying human capital distribution of adults $F(h)$ follows a log-normal distribution

$$\log(h) \sim F(h) = \mathcal{N}(\mu, \sigma^2)$$

The log-normality of the human capital distribution is a condition that I will verify in the equilibrium. Because human capital is endogenously formed, the values of μ and σ^2 are both equilibrium objects in the steady state.

Let $\bar{h}_1$ denote the average human capital of teachers. I define a measure of average teacher quality ξ as the z-score of $\log(\bar{h}_1)$ in the population, i.e.,

$$\xi \equiv \frac{\log(\bar{h}_1)-\mu}{\sigma} \tag{1}$$

2.2 Human Capital Formation

After the occupation selection stage, adult workers have children[2] and solve the following maximization problem

$$\max_{c,e\geq 0} \ \log(c) + \beta\mathbb{E}_\epsilon \log(h')$$

subject to budget constraint

$$c + e = y = h^{\psi_2}$$

[2] I assume that only workers have children for analytical tractability of the model. I do not think that including teachers' children in this stage will change the results significantly because teachers account for less than 5% of the adult population.

and human capital production function

$$\log(h') = A + \underbrace{\log(\epsilon)}_{\text{normal dist.}} + \underbrace{\delta_0\xi + \delta_1 \log(e) + \delta_2 \log(e)\xi}_{\text{translog}} + \underbrace{\rho \log(h)}_{\text{residual persistence}} \tag{2}$$

where c is consumption, e is education investments, h' is children's human capital, and ϵ is an idiosyncratic shock that follows log-normal distribution

$$\log(\epsilon) \sim \mathcal{N}(-\sigma_\epsilon^2/2, \sigma_\epsilon^2)$$

so that $\mathbb{E}(\epsilon) = 1$.

I assume that average teacher quality ξ and parental investments e interact in the human capital production function (2) in a translog fashion.[3] Parameter δ_2 governs whether they are gross complements or substitutes. I also allow for a direct spillover effect of parents' human capital to the next generation governed by ρ.

Because teachers are heterogeneous in the model, the human capital production function (2) should be interpreted as a reduced-form way of modeling how parental inputs and teachers' human capital jointly determine children's outcome without explicitly micro-founding the assignment problem (Sattinger 1975, Seshadri 2000). Beyond purchasing books and computers, the role of $\delta_1 \log(e)$ reflects parents' efforts in matching their own children to better teachers in the economy. Likewise, the interaction term $\delta_2 \log(e)\xi$ captures the idea that need to compete for better teachers varies as the total amount of teaching resource changes.

2.3 Discussions

There are several points worth noting here regarding the modeling choices on occupation selection and teacher quality.

First, I have assumed that individuals differ by a one-dimensional human capital h and an idiosyncratic taste shock ν. Human capital here summarizes a broad set of per-

[3] One can also view the translog production function as the Kmenta (1967) approximation to the more commonly-used CES production function.

sonal traits that affect productivities, including but not limited to cognitive ability, non-cognitive ability, experience, and education. An alternative modeling choice is to use a multi-dimensional human capital model à la Roy (1952) where individuals have comparative advantage in one of the occupations (Borjas 2002, Bacolod 2007). With strong positive correlation between different abilities, the Roy-style model offers the same intuition on the selection effects. Such a model, however, requires us to model separate production functions for each dimension of human capital and the corresponding mappings to productivities across occupations. In the current analysis, I restrict to the one-dimensional case for data availability reasons, but I acknowledge that the quantitative results will be smaller if *relative to* overall earnings, skills that are more important in the teaching profession (e.g., communication and interpersonal relation skills) are less affected by changes in human capital production inputs.

To investigate this concern further, I collect data on the importance of five cross-functional skills by occupation from O*NET, including complex problem solving skills, resource management skills, social skills, system skills, and technical skills. I find that for each skill, the value of teachers are all within one standard deviation of the values across other non-teaching occupations (see Table 1). Thus, I do not expect including multi-dimensional human capital will change the results significantly.

Table 1: Skill Importance by Occupation

	Teacher	Non-Teachers	
	Value	Mean	Standard Deviation
Complex Problem Solving Skills	3.53	3.19	0.50
Resource Management Skills	2.40	2.39	0.66
Social Skills	3.27	2.89	0.52
System Skills	3.17	2.85	0.60
Technical Skills	1.45	1.93	0.79

Notes: This table displays the importance of each cross-functional skills by teachers and non-teachers in the O*NET dataset.

Second, in our definition teacher quality ξ reflects the *relative* position of teachers' human capital in the population. In other words, parallel shifts in the population-wide human capital distribution, i.e., changes in μ, does not affect teacher quality ξ. I use this definition to emphasize the selection channel and its amplification mechanisms. Our results will be stronger if teacher quality also depends on the absolute level of teachers' human capital because there will be an additional feedback loop where teacher quality feeds back on average human capital in the population and so on.

Third, I have adopted a rather stylized model of occupation selection. To focus on the propagation mechanism through endogenous human capital formation, I have abstracted away from some important margins in the context of teacher selection and quality such as the role of risk preferences (Cortes and Pan 2018), dynamic learning (Rothstein 2015), the allocation of teachers across schools or districts (Biasi et al. 2021), and teacher efforts (Bold et al. 2017). I view these possibilities as intriguing avenues for future research.

2.4 Model Solution

The share of adults that becomes teachers by human capital h is given by

$$l(h) = \frac{(w\kappa h^{\psi_1 - \psi_2})^\theta}{1 + (w\kappa h^{\psi_1 - \psi_2})^\theta} \approx (w\kappa h^{\psi_1 - \psi_2})^\theta$$

Integrating $l(h)$ across the human capital distribution $F(h)$, the aggregate share of teachers π is

$$\pi = \int l(h)\, dF(h) = (w\kappa)^\theta \cdot \exp\left(\mu(\psi_1 - \psi_2)\theta + \frac{((\psi_1 - \psi_2)\sigma\theta)^2}{2}\right)$$

Using the definition in Equation (1), teacher quality ξ can be solved as

$$\xi = (\psi_1 - \psi_2) \cdot \sigma\theta \tag{3}$$

Equation (3) is important as it shows that teacher quality depends on three objects. First, the relative skill bias across sectors $\psi_1 - \psi_2$ represents the selection mechanism.

If the relative return to human capital between teaching and non-teaching occupation rises, teacher quality ξ improves. Second, teacher quality is proportional to the dispersion of human capital among potential teachers σ. This captures the idea that selection is powerful when agents become more heterogeneous. Last, teacher quality also depends on θ which reflects the elasticity that individuals move across occupations in response to changes in valuations. The novel part of the model is to recognize that in a dynamic environment, σ is an endogenous object. In light of this, Equation (3) also provides a decomposition formula that will be used in later analysis:

$$\underbrace{d\log(\xi)}_{\text{change in teacher quality}} = \underbrace{d\log(\psi_1 - \psi_2)}_{\text{change in selection}} + \underbrace{d\log(\sigma)}_{\text{change in h.c. dispersion}} \tag{4}$$

Now I turn to optimal individual decisions. For interior solutions of e, the optimal investment to income ratio is

$$\frac{e}{y} = \frac{\beta(\delta_1 + \delta_2\xi)}{1 + \beta(\delta_1 + \delta_2\xi)} \approx \beta(\delta_1 + \delta_2\xi)$$

Substitute e back into the human capital production function, we have

$$\log(h') = A + \log(\epsilon) + f(\xi; \vec{\delta}) + (\rho + \psi_2(\delta_1 + \delta_2\xi)) \log(h) \tag{5}$$

where $\vec{\delta} = \{\delta_0, \delta_1, \delta_2\}$ and

$$f(\xi; \vec{\delta}) = \delta_0\xi + (\delta_1 + \delta_2\xi) \cdot \log(\beta(\delta_1 + \delta_2\xi))$$

The dynamics of Equation (5) indicate that when $\log(h)$ is normal, $\log(h')$ stays normal. The transition path of human capital distribution is therefore analytically characterized:

$$\begin{cases} \mu' = A + f(\xi; \vec{\delta}) + (\rho + \psi_2(\delta_1 + \delta_2\xi)) \cdot \mu - \sigma_\epsilon^2/2 \\ (\sigma')^2 = (\rho + \psi_2(\delta_1 + \delta_2\xi))^2 \cdot \sigma^2 + \sigma_\epsilon^2 \\ \xi = (\psi_1 - \psi_2) \cdot \sigma\theta \end{cases} \tag{6}$$

The system in (6) has a close relationship to Benabou (2002) which exploits the properties of the normal distribution to study the relationship between tax and education policies. The key difference here is the third equation in (6) where teacher quality ξ is an endogenous object and enters the evolution of human capital. As a result, changing ψ_1 or ψ_2 has dynamic implications through ξ and endogenous human capital distribution.

Equation (6) also highlights the key role that δ_2 plays in determining whether teacher quality is amplified or dampened when the dispersion of human capital σ is endogenous. Consider a small decrease of ξ and focus on how σ' changes. If $\delta_2 < 0$, then the intergenerational persistence $(\rho+\psi_2(\delta_1+\delta_2\xi))$ is higher and we have higher σ'. This feeds back to the determination of teacher quality in the next period and leads to further declines in ξ'. On the other hand, σ' will be smaller when teacher quality decreases when $\delta_2 > 0$. Therefore, relating back to the human capital production function in Equation (2), endogenous human capital amplifies (dampens) changes in selection if and only if teacher quality is gross substitute (complement) to parental investments.

3. Identification and Calibration

In this section, I carry out the calibration of the model by proving identification and finding empirical counterparts to the model's predictions.

3.1 Model Identification

The objects that need to be identified include

$$\underbrace{\delta_0, \delta_1, \delta_2, A, \rho, \sigma_\epsilon^2}_{\text{h.c. technologies}}, \underbrace{\kappa, \theta, \beta}_{\text{preferences}}, \underbrace{\psi_1, \psi_2}_{\text{labor market}}, \underbrace{\xi, w, \mu, \sigma^2}_{\text{endogenous objects}}.$$

The steady-state of the model can be summarized in the following equations:

$$\frac{\mathbb{E}(y_1)}{\mathbb{E}(y_2)} = w \cdot \exp\left(\mu(\psi_1 - \psi_2) + \frac{\sigma^2}{2}(\psi_1 - \psi_2)(\psi_1 + \psi_2 + 2\psi_1\theta)\right) \tag{7}$$

$$\text{CV}(y_1) = \sigma\psi_1 \tag{8}$$

$$\text{CV}(y_2) = \sigma\psi_2 \tag{9}$$

$$\pi = (w\kappa)^{\theta} \cdot \exp\left(\frac{\mu\xi}{\sigma} + \frac{\xi^2}{2}\right) \tag{10}$$

$$\xi = (\psi_1 - \psi_2) \cdot \theta\sigma \tag{11}$$

$$\text{IGE} = \rho + \psi_2(\delta_1 + \delta_2\xi) \tag{12}$$

$$\sigma^2 = \frac{\sigma_\epsilon^2}{1 - \text{IGE}^2} \tag{13}$$

$$\mu = \frac{A + \delta_0\xi + (\delta_1 + \delta_2\xi) \cdot \log\left(\frac{e}{y}\right) - \sigma_\epsilon^2/2}{1 - \text{IGE}} \tag{14}$$

$$\frac{e}{y} = \beta(\delta_1 + \delta_2\xi) \tag{15}$$

where $\text{CV}(x)$ denotes the coefficient of variation of variable x and IGE denotes intergenerational elasticity of earnings when both parent and children work as non-teachers.

I can measure $\mathbb{E}(y_1), \mathbb{E}(y_2), \text{CV}(y_1), \text{CV}(y_2), \pi, \text{IGE}, e/y$ in the data - more details below. Because the unit of human capital is undetermined, I have the freedom to make one normalization. After normalizing $\psi_2 = 1$, I need more information because there are 14 unknowns with 9 equations.[4] I can gather additional information from the model's comparative statics regarding a small change to teacher market rigidity ψ_1:

$$\frac{\partial\overline{\log(y')}}{\partial\psi_1} = \psi_2 \cdot \underbrace{\sigma\theta}_{\frac{\partial\xi}{\partial\psi_1}} \left[\underbrace{\delta_0 + \delta_2\log\left(e/y\right) + \psi_2\delta_2\mu}_{\text{direct}} + \underbrace{\beta\delta_2 \cdot \frac{\delta_1 + \delta_2\xi}{e/y}}_{\text{indirect}}\right] \tag{16}$$

$$\frac{\partial^2 \log y'}{\partial\psi_1\partial\log y} = \sigma\theta \cdot \psi_2 \cdot \delta_2 \tag{17}$$

$$\frac{\partial\mathbb{E}(y_1)}{\partial\psi_1} = \mathbb{E}(y_1) \cdot \left(\mu + \sigma^2(\psi_1 + \theta(2\psi_1 - \psi_2))\right) \tag{18}$$

$$\frac{\partial\pi}{\partial\psi_1} = \pi \cdot (\theta\mu + \sigma\theta\xi) \tag{19}$$

where y' denotes the average earnings of the next generation.

Equation (16) and (17) quantify how changes in ψ_1 affect income in the next gener-

[4]Normalizing $\psi_2 = 1$ is without loss of generality. It is equivalent to normalizing ψ_1, σ_ϵ, or A.

ation. In (16), the effect on next generation's average income combines a direct effect coming from changes in teacher quality ξ and an indirect effect capturing parents' responses through endogenous investments e. Equation (17) highlights that the key parameter δ_2 is identified from the differential impacts across parents with different income. On the other hand, Equations (18) and (19) quantifies how changes in ψ_1 affect teacher employment and outcome.

With these additional information, the identification argument is presented next.

Proposition 1: The model is identified up to the calibration of ρ if we observe $\mathbb{E}(y_1)$, $\mathbb{E}(y_2)$, CV(y_1), CV(y_2), π, IGE, e/y and measure the left-hand-sides of Equations (16)-(19).

Proof. Given that $\psi_2 = 1$, Equation (9) identifies σ; then Equation (8) identifies ψ_1; Equation (13) identifies σ_ϵ. Combining Equations (18) and (19) by substituting out μ identifies θ. Then, Equation (11) identifies ξ; Equation (19) identifies μ; Equation (7) identifies w; Equation (10) identifies κ; Equation (17) identifies δ_2; Equation (12) identifies δ_1 given that I calibrated ρ; Equation (15) identifies β; and lastly Equation (14) identifies A. $\square$

3.2 Empirical Evidence

I measure the left-hand-sides of Equations (16)-(19) using the variations coming from the passage of duty-to-bargain (DTB) laws across states between 1960 and 1996.

Prior to 1960, teachers' unions in the United States played little role in the negotiation of contracts between teachers and school district and collective bargaining took place in only some large, urban school districts. Beginning with Wisconsin in 1960, however, states start to pass pubic sector duty-to-bargain (DTB) laws, which mandated that districts have to negotiate in good faith with a union that has been elected for the purposes of collective bargaining. These laws gave considerable power to teachers' unions in the collective bargaining process, leading to a sharp rise in teacher unionization and collectively bargained contracts.

To examine the (differential) effects of DTB laws on the next generation's human capital and income, Lovenheim and Willén (2019) run the regression

$$Y_i = \alpha_1 \cdot \text{DTB exposure}_i + \zeta X_i + \varepsilon \tag{20}$$

using individual-level data from the American Community Survey (ACS). They find that a 10-year exposure to teachers under DTB laws reduces annual earnings by 2.36% (averaging men and women). Moreover, compared with Black and Hispanic children, the negative effects are 4.9 percentage points smaller among White and Asian children, whose parents had 60% higher income after adjusting for the number of children (calculated using data from the Current Population Survey (CPS) March Supplement). Similar findings are also reported in Tincani (2021) where the authors finds that tying public school teacher wages to skills and introducing minimum competency requirement for teacher reduce the achievement gap between the poorest and richest 25% of students by a third.

Complementing their findings on children's earnings, I run additional regressions to measure Equations (18) and (19). In particular, I collect data on full-time workers from the CPS-ASEC, categorize whether individuals are teachers or not based on occupation codes, and use standard two-way fixed effects methods to examine the how duty-to-bargain laws affect employment share and teacher earnings statistics

$$Y_{\text{state,year}} = \alpha_2 \cdot \text{DTB}_{\text{state,year}} + \text{State FE} + \text{Year FE} + \varepsilon \tag{21}$$

where observations are at state-year level. The regression results are shown in Table 2.

I find that DTB laws have negative (but statistically insignificant) effects on average earnings of teachers $\mathbb{E}(y_1)$ while reducing the coefficient of variations of teacher earnings by 0.03 from a base of 0.56. In addition, DTB laws reduce teacher employment share by 0.35 percentage points from a base of 4.6%. These findings are consistent with the literature that uses the recent expiration of collective bargaining agreements in some states as a source of exogenous variation. In particular, Biasi et al. (2021) shows that introducing flexible pay scheme attracted teachers from other school districts, raised the salaries of high-quality teachers, increased teacher pay dispersion measured by the

Table 2: Regression Results

	(1) Teacher share	(2) CV(teacher)	(3) Average teacher earnings
DTB	-0.351**	-0.0292*	-591.3
	(0.110)	(0.0138)	(425.4)
# Observations	1378	1364	1378

Notes: This table displays the results of regression (21). Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Average teacher earnings is measured in year 2000 dollars.

coefficient of variation, and resulted in higher teacher quality.

Overall, the regression results are consistent with the interpretation that these laws mainly affect teacher market by changing rigidity parameter ψ_1. One potential worry is that variations in employment and wages could also reflect other effects of DTB laws, such as changes in relative wages w or entry barriers κ. I provide a detailed discussion about how this possibility affects the identification and our results in Section 5.

To utilize these estimates, I revisit Equations (16)-(19) and rewrite them as:

$$\frac{\Delta\overline{\log(y')}}{\Delta\psi_1} = \text{CV}(y_2) \cdot \theta \left[\delta_0 + \delta_2 \log(e/y) + \psi_2\delta_2\mu + \beta\delta_2 \cdot \frac{\delta_1 + \delta_2\xi}{e/y}\right] \tag{16'}$$

$$\frac{\Delta^2 \log y'}{\Delta\psi_1 \Delta \log y} = \theta\delta_2 \cdot \text{CV}(y_2) \tag{17'}$$

$$\frac{\Delta \log(y_1)}{\Delta\psi_1} = \mu + \sigma^2(\psi_1 + \theta(2\psi_1 - \psi_2)) \tag{18'}$$

$$\frac{\Delta\pi}{\pi\Delta\psi_1} = \theta\mu + \sigma\theta\xi \tag{19'}$$

The regression results in Table 2, together with the estimates in Lovenheim and Willén (2019), inform the left-hand-sides of these equations. In addition, the magnitude of changes in ψ_1 can be measured using changes in the coefficient of variations in teachers' earnings:

$$\Delta\psi_1 = \psi_1 \cdot \frac{\Delta\text{CV}(y_1)}{\text{CV}(y_1)} \tag{22}$$

3.3 Calibration Results

I calibrate $\rho = 0.6 \times$ IGE following the results in Lefgren et al. (2012). It represents a "measure of ignorance" in our understandings of the determinants of intergenerational mobility. Other target moments, including $\frac{\mathbb{E}(y_1)}{\mathbb{E}(y_2)} = 0.96$, CV$(y_1) = 0.56$, CV$(y_2) = 0.77$, $\pi = 4.6\%$, IGE $= 0.36$, and $e/y = 0.05$, are derived from the Current Population Survey (CPS), the Panel Study of Income Dynamics (PSID), and the past literature on parental investments in children's education (Lee and Seshadri 2019, Daruich 2018) for years closest to 2000. Because the model is just identified, these data moments will be exactly matched in the calibration procedure following Proposition 1.

Table 3: Calibration Results

	Human capital formation parameters	Value
δ_0	teacher effect (level)	-0.48
δ_1	investment effect	-0.42
δ_2	teacher effect (gradient)	-0.88
A	TFP of h.c. production	1.12
ρ	residual persistence	0.22
σ_ϵ	ability shock dispersion	0.72

	Labor market parameters	Value
ψ_1	skill bias (teachers)	0.73
ψ_2	skill bias (non-teachers)	1

	Preference parameters	Value
κ	teacher cost	0.21
θ	taste shock dispersion	3.07
β	weight on children's h.c.	0.35

	Equilibrium objects	Value
ξ	teacher quality	-0.64
w	relative wage	2.18
μ	average h.c.	1.15
σ	h.c. dispersion	0.77

Notes: This table displays the calibration results. See text for the identification and target moments.

The parameters of particular interest are those in the human capital production function. Combining the results on $\{\delta_0, \delta_1, \delta_2\}$ with the observed level of e/y, I find that a one standard deviation change of teacher quality throughout ones' education leads to a rise in human capital by 1.6 percent. The implied result from the structural model here is slightly larger but broadly consistent with Chetty et al. (2014a), who conclude that "a one standard deviation increase in teacher quality in a single grade raises annual earnings by 1.3 percent." The result that $\delta_2 < 0$ is of particular importance because as discussed before, it implies that the endogenous human capital formation serves as an amplifying mechanism of the teacher selection channel. The result that $\delta_2 < 0$ is also consistent with existing estimates on the substitutability of public and private investments (Kotera and Seshadri 2017, Yum 2023) and the idea that public schooling serves as the "great equalizer" in the economy (Agostinelli et al. 2022).

4. Counterfactual Analyses

In this section, I analyze two counterfactual to better understand the role of teacher quality and human capital formation in shaping the dynamics of inequality and intergenerational mobility.

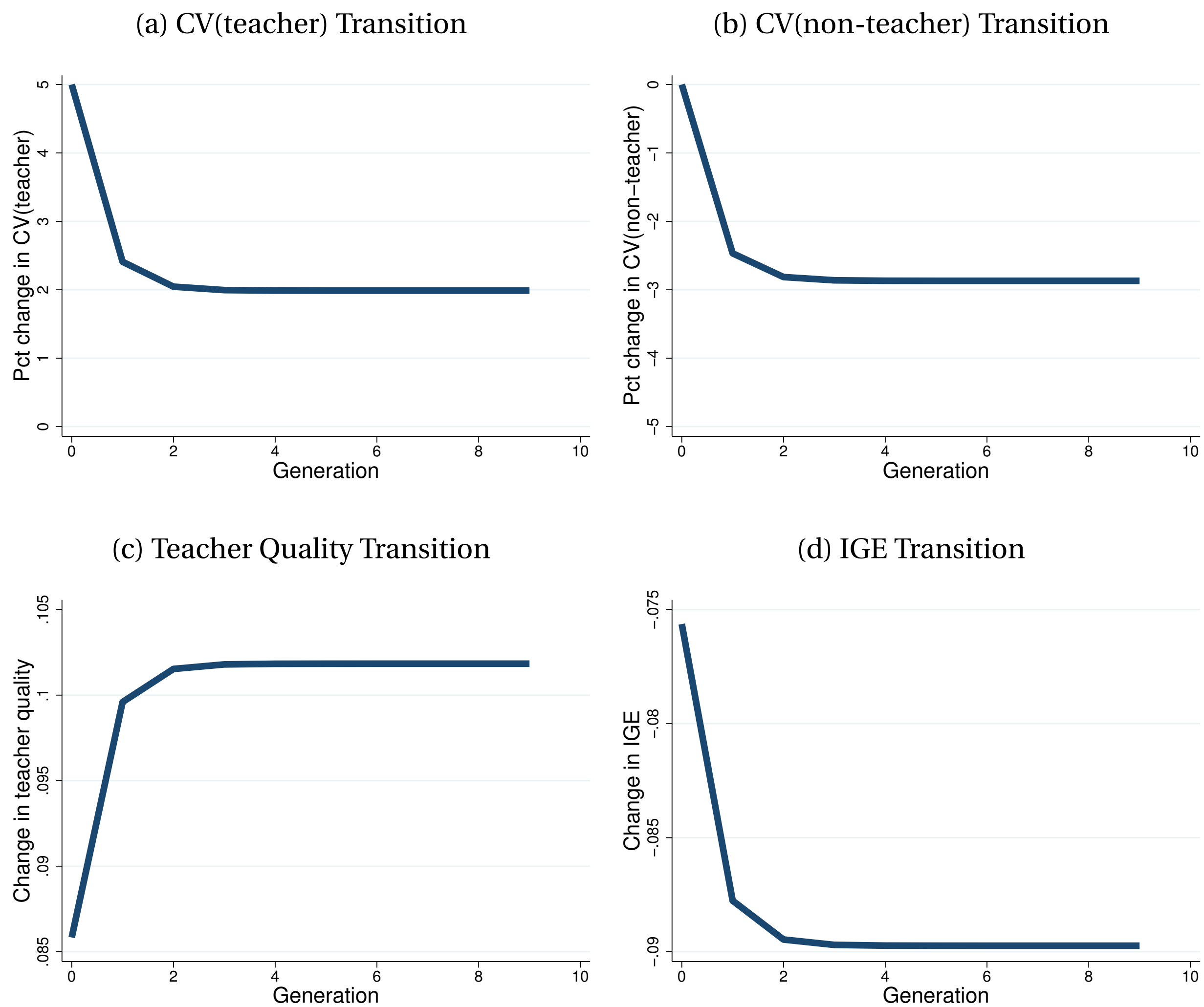
4.1 Performance-Based Compensation

In the first counterfactual, I permanently increase the returns to human capital by 5% in the teaching profession to mimic a performance-based compensation. The magnitude of 5% is chosen to be the same as the initial impacts that duty-to-bargain laws had on the income dispersion among teachers in the empirical findings, albeit in a different direction. Figures 1a to 1d shows the transition path of CV(teacher), CV(non-teacher), teacher quality ξ, and IGE from the original economy to the new steady state.

I find that inequality within the teaching profession jumps initially. But in the long-run steady-state, only two-fifth of the initial impacts on CV(teacher) survive. In contrast, CV(non-teacher) decreases drastically by 3%, reflecting changes in the dispersion of human capital σ. Intergenerational elasticity of earnings falls from 0.36 to 0.27, due to the fact that higher teacher quality diminishes the role of private parental investments and hence intergenerational persistence of human capital.

The results also indicate that the magnitude of these effects vary along the transition path. In particular, empirical analyses that focus on short-run effects, i.e., $t = 0$ or $t = 1$, could overstate the effects of performance-based compensation on CV(teacher) and understate the dynamic effects on teacher quality ξ, non-teacher inequality CV(non-teacher), and intergenerational mobility IGE.

Figure 1: Counterfactual Results on Increasing Teacher Wage Rigidities



Notes: These figures plot the transition path of CV(teacher), CV(non-teacher), teacher quality ξ, and IGE following a 5% permanent reduction of ψ_1 in the steady-state economy.

4.2 Skill-Biased Technical Change

In the second counterfactual, instead of changing ψ_1, I let ψ_2 rise by 1% permanently to mimic a small skill-biased technical change (SBTC), i.e., the "convexification" of the non-teaching labor market (Autor et al. 2020). Figures 2a to 2d shows the transition path of CV(teacher), CV(non-teacher), teacher quality ξ, and IGE from the original economy to the new steady state.

I find that when ψ_2 increases, it not only raises inequalities within non-teachers but also those within teachers, reflecting changes in σ. Higher returns to human capital in non-teaching occupations attract the most talented workers and reduce teacher quality, with the effects being much larger in the long run (see Figure 2a). Interestingly, intergenerational elasticity of earnings increases for two reasons. The first reason is the same as that in the previous counterfactual - reduced teacher quality raises the role of parental investments and hence intergenerational persistence. The second reason is that the dispersion of parental income is also greater due to higher ψ_2, magnifying disparities in parental investments.

To better understand the relative importance of these different channel, I conduct a model-based decomposition of $\text{CV}(y_2)$ in the following steps:

1. First, because $\text{CV}(y_2) \equiv \sigma\psi_2$, I decompose $\text{CV}(y_2)$:

$$\underbrace{\text{CV}(y_2)' - \text{CV}(y_2)}_{\text{changes in inequality}} = \underbrace{\sigma'(\psi_2' - \psi_2)}_{\text{direct effect}} + \underbrace{(\sigma' - \sigma)\psi_2}_{\text{indirect h.c. dist.}}$$

   I find that the direct effect of changing ψ_2 accounts for 48% of total changes in $\text{CV}(y_2)$ in the long run, with the rest being explained by changing σ.

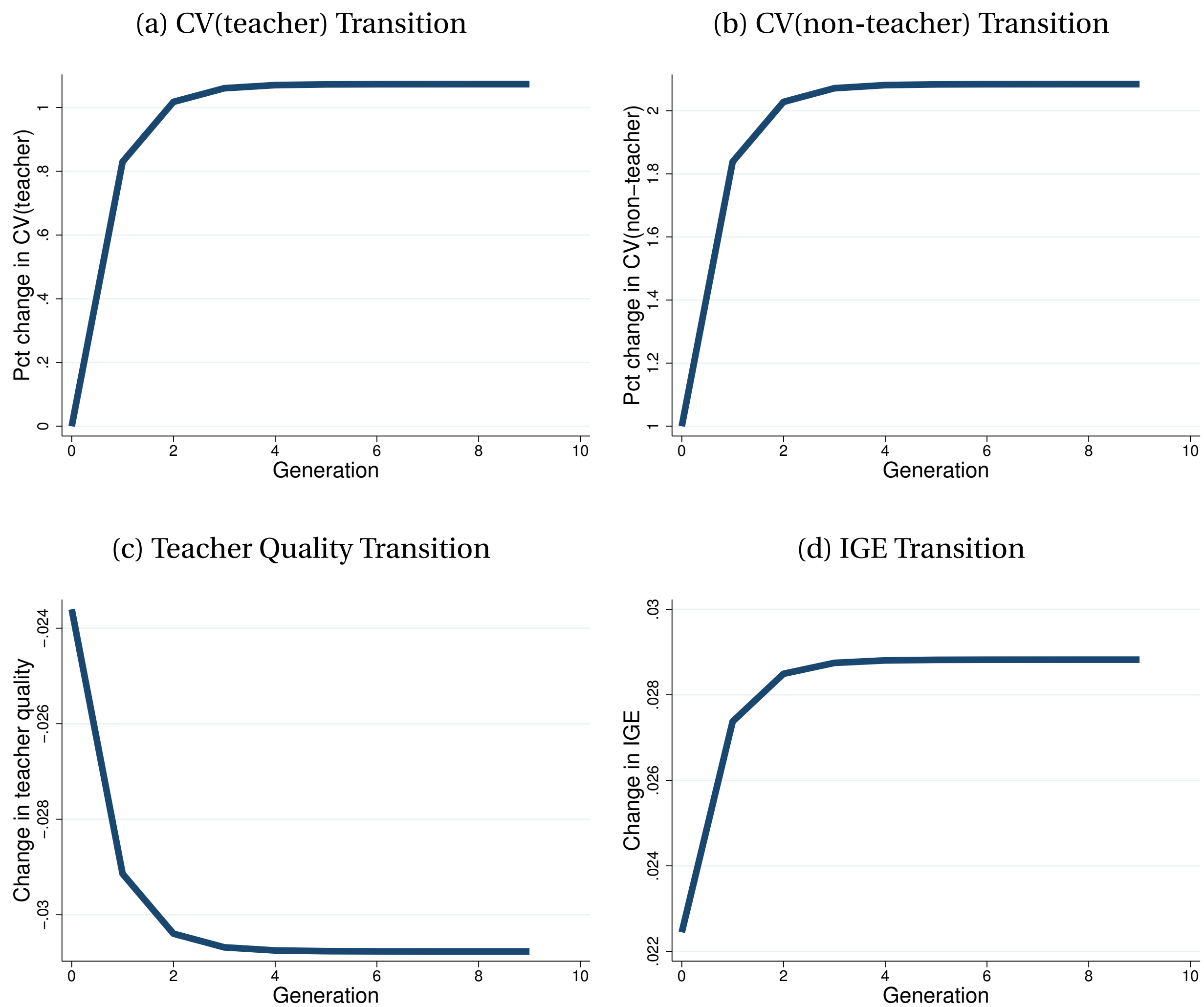
2. To understand what drives changes in σ, I conduct a decomposition of IGE because in the steady-state σ is proportional to $\sqrt{1 - \text{IGE}^2}$. The formula $\text{IGE} = \rho + \psi_2(\delta_1 + \delta_2\xi)$ motivates the following decomposition:

$$\underbrace{\psi_2'(\delta_1 + \delta_2\xi') - \psi_2(\delta_1 + \delta_2\xi)}_{\text{changes in IGE}} = \underbrace{\psi_2\delta_2(\xi' - \xi)}_{\text{teacher quality}} + \underbrace{(\delta_1 + \delta_2\xi')(\psi_2' - \psi_2)}_{\text{parental income}}$$

   I find that teacher quality channel accounts for 94% of changes in IGE with the rest being explained by changes in parental income dispersion.

These decomposition results lead to an intriguing policy implication. Suppose ψ_2 increases by 1%, one can counteract its contemporaneous effects on teacher quality by

Figure 2: Counterfactual Results on Skill-Biased Technical Change



Notes: These figures plot the transition path of CV(teacher), CV(non-teacher), teacher quality ξ, and IGE following a 1% permanent increase in ψ_2 in the steady-state economy.

also raising ψ_1 by 1%. But with the additional channel through parental income, this 1% increase is not enough to maintain teacher quality in later periods. Therefore, to neutralize the effects of the SBTC, the returns to human capital in the teaching profession needs to rise *relatively more* than that in the non-teaching profession. If instead, policymakers or teacher unions shield teachers from rising inequality elsewhere by reducing ψ_1, income inequalities among non-teachers will become even more severe in the future.

5. Robustness

In this section, I discuss the robustness of the main results.

5.1 Mapping DTB Laws to the Model

As discussed before, one potential worry is that variations in employment and wages following DTB laws could also reflect changes in relative wages w or entry barriers κ. In that case, instead of Equations (18') and (19'), we have

$$\begin{cases} \Delta \log(y_1) = \Delta\psi_1[\mu + \sigma^2(\psi_1 + \theta(2\psi_1 - \psi_2))] + \Delta w \\ \Delta\pi = \Delta\psi_1 \cdot (\theta\mu + \sigma\theta\xi) + \theta(\Delta w + \Delta\kappa) \end{cases} \tag{23}$$

Note that potential changes in w and κ does not affect the interpretation of other equations including (16'), (17'), and (22) because they do not alter teacher quality ξ in the model. They, however, do affect the calibration of other parameters. I divide the analysis into three cases.

First, suppose DTB laws affect entry barriers κ but not relative wage w. Then Equation (18') survives but equation (19') is contaminated because I do not have a direct measure of $\Delta\kappa$ in the data. In this case, I need to calibrate θ outside of the model and choose a value from the literature. An important insight here is that different value of θ does not affect the calibration of other variables except $\{\delta_0, \delta_2, \xi, w, \kappa\}$, and the results in all counterfactuals remain unchanged.

To see this, suppose θ is doubled. To make Equation (17') hold, δ_2 needs to halve. Similarly, δ_0 needs to halve to make Equation (16') hold. ξ needs to double because $\xi = (\text{CV}(y_1) - \text{CV}(y_2)) \cdot \theta$. Lastly, w and κ needs to adjust to maintain Equations (7) and (10). Beyond that, no other parameters need to change because δ_0, δ_2, and ξ enter the rest of the model, especially human capital dynamics, in a multiplicative fashion and these changes exactly cancel out.

Second, suppose DTB laws affect w but not κ. I can multiply the first equation in (23) by θ and subtract the second equation to cancel out Δw. Then, I can proceed like the previous case by calibrating θ exogenously. The results in counterfactuals are not affected.

Last, suppose DTB laws affect w as well as κ. Then the empirical results on how DTB laws affect teacher labor markets are not informative about parameters and I need to find additional calibration targets. One option is to equate the effects of a one standard deviation increase in teacher quality on children's income, which is $(\delta_0 + \delta_2 \log(e/y)) \cdot \psi_1$ in the model, to existing empirical estimates (e.g., Chetty et al. 2014a). Then, I can calibrate θ exogenously, and the counterfactual results are again not affected. As discussed before, when I compare teacher value added in the model to Chetty et al. (2014a) after calibration, the two values are quite similar.

To sum up, while potential changes in w and κ threaten the identification of θ, the counterfactual results will not be affected if I calibrate θ exogenously outside of the model.

5.2 Heterogeneous Preference

In the baseline model, I have assumed that the idiosyncratic preference shock ν is not correlated with human capital h. Suppose instead there is a systematic relationship between taste and human capital, consider

$$\nu = \psi_3 \log(h) + \tilde{\nu}$$

where ψ_3 governs the degree of correlation and $\tilde{\nu}$ is an idiosyncratic shock.

Then, individual's choice problem becomes

$$\max_{j \in \{1,2\}} \mathbb{1}_{j=1}(\log(wh^{\psi_1} \cdot \kappa \cdot h^{\psi_3}) + \tilde{\nu}) + \mathbb{1}_{j=2} \log(h^{\psi_2})$$

This leads to changes in the formulas of π and ξ where ψ_1 needs to be replaced by $\psi_1 + \psi_3$, which also implies that there is an additional parameter ψ_3 to be calibrated.

One solution is to equate the effects of a one standard deviation increase in teacher quality on children's income, which is $(\delta_0 + \delta_2 \log(e/y)) \cdot (\psi_1 + \psi_3)$ in this case, to existing empirical estimates (e.g., Chetty et al. 2014a). This gives an additional condition that allows us to separately identify ψ_3 from ψ_1 (which is identified using the dispersion of teachers' earnings). As discussed before, when I compare teacher value added in the model to Chetty et al. (2014a) after calibration, the two values are quite similar. This implies that the main results will not be significantly affected if I allow this form of correlation between preference and human capital.

6. Conclusion

In this paper, I study how teacher selection affects inequality and intergenerational mobility. In a model with occupation choice and child investments, I investigate the feedback mechanism between teacher quality and human capital distribution. Human capital dispersion amplifies the selection channel in determining teacher quality, and teacher quality affects the degree of dispersion itself through human capital formation. The model is identified using empirical evidence on how duty-to-bargain laws affect teacher labor market and children's long-run outcomes. In counterfactuals, I find that tying compensation to performance in the teaching profession raises income inequality among teachers but reduces inequality among non-teachers and improves intergenerational mobility. Teacher labor market also plays an important role in propagating aggregate shocks. In particular, I find that reducing teacher pay rigidities could alleviate the effects of skill-biased technical change on inequalities.

Lastly, I want to suggest that while this paper studies teacher quality, the same argument holds for other occupations, especially those employed in the public sector, as long as worker quality spills over to the productivity of future generations. These effects can be quantified in the same way through combining structural modeling and empirical analysis. I leave this as interesting future avenues of research.

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