On the Economic Content of the Gini Coefficient [*]

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Abstract

This paper argues that the canonical assignment model, which is widely used in the study of wage determination, provides natural links to the standardized tools of inequality analysis, such as the Lorenz curve and the Gini coefficient. I show that an intuitive formula for the Gini coefficient of earnings can be derived using a standard assignment model. Such a model is useful in understanding the potential sources of earnings inequality, since it formulates the Gini coefficient as a function of the dispersion of worker skills, the distribution of firm productivities, and the strength of complementarities in production between capital and labor. The Gini coefficient increases with the dispersion of skills, the dispersion of productivities, and the labor share.

Keywords: Gini coefficient, earnings inequality, earnings equation, the assignment model.

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1. Introduction

This paper provides an economic interpretation of the Gini coefficient in a formal setting. Using the general framework developed by Tumen (2011), which builds on Sattinger's assignment model with two-sided heterogeneity [see Sattinger (1979, 1993)], a Gini coefficient for the distribution of earnings is derived. Formulating the Gini coefficient within such an assignment model serves two purposes. First, it allows us to think of earnings inequality as a byproduct of the optimal allocation of workers across firms. This is yet another affirmation of equity and efficiency being different concepts. Second, it allows us to analyze earnings inequality by separately characterizing the contribution of each economic parameter. The Gini coefficient is formulated as a combination of the following elements: **(i)** distribution of skills across workers (supply of skills), **(ii)** distribution of productive capital across firms (demand for skills), **(iii)** characteristics of the production technology that each firm uses, and **(iv)** properties of the mechanism ensuring an optimal resource allocation in the economy.

I conclude that the interactions between an increased relative supply of skills and an increased relative demand for skills change the Gini coefficient for the distribution of earnings. The direction of the change depends on the shape and the curvature of the earnings function. To be specific, when the earnings function is convex and increasing in skills – as suggested by the empirical evidence – the model generates two key mirror-image results: an increased relative demand for skills raises the Gini coefficient, as does an increased relative supply of skills.

The proposition that interactions between the demand for skills – which has often been associated with the skill-biased technical-change hypothesis – and the supply of skills determine the degree of earnings inequality is the subject of many papers, including Katz and Murphy (1992), Juhn, Murphy, and Pierce (1993), and Card and Lemieux (2001).[1] Similar to the majority of the papers in this literature, this paper makes predictions about the co-evolution of earnings inequality and the demand and supply conditions for workers of different skill categories. It differs from its predecessors in that it presents the source of earnings inequality as a matching technology that optimally assigns workers to firms in a top-down structure (i.e., with positively

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[1]   There is a strand of literature, the "revisionists," who argue that earnings inequality is an episodic event [see Lee (1999), Card and DiNardo (2002), and Lemieux (2006)]. Autor, Katz, and Kearney (2008) and Dustmann, Ludsteck, and Schoenberg (2009) reconcile these two views.

assortative matching). I show that the Gini coefficient is directly computable within such a framework.

The main contribution of this paper can be summarized as follows. The canonical assignment model provides a simple framework for analyzing the effect of inequalities among workers' and firms' abilities on the formation of wages. I show that this framework has a natural link – with easy closed-form formulas – to the universally accepted measures of inequality, such as the Lorenz curve and the Gini coefficient. This may improve our understanding of earnings inequality, as it provides us with a simple tool to explicitly formulate the Gini coefficient as a function of the inequality in workers' skills, inequality in firms' productive capacities, and the strength of complementarities between capital and labor in an economy. With the method I have developed, it is possible to independently analyze the effect of a change in the dispersion of skills, the distribution of productivities, or the strength of complementarities on the Gini coefficient. The link to the Gini coefficient is particularly important, since the time-series evolution of Gini coefficients (for incomes) is readily available for many countries. Putting the data and this method together, one can use the actual evolution of the Gini coefficient to arrive at useful results on the evolution of the sub-components of earnings inequality, which may have valuable as well as practical policy implications.

The paper is organized as follows. Section 2 develops the model. Section 3 presents the main results, derives the Gini coefficient, and relates the main results to various literatures. Section 4 is the conclusion.

2. The Model

There are two factors of production: capital and labor. Firms differ in the amount of productive capital they have. Workers differ in the amount of skills they own. Let c be the capital endowment of each firm and G_c be the cumulative density of firms with respect to capital. Similarly, let x be the level of worker skills and G_x be the cumulative density of workers with respect to skills.[2] Both densities are monotone, strictly increasing, continuous, and have positive support. There are no consumer preferences. There is a one-to-one match between workers and employers. Let $q(c,x)$ be the output produced by a type-c firm employing a type-x worker. The production function $q(c,x)$ is twice continuously differentiable in c and x, with $q_c > 0$, $q_x > 0$,

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[2]   For analytical tractability, we assume that the productive capacity of a firm and the skills of a worker are both univariate (rather than being multi-dimensional vectors).

$q_{cc} < 0$, and $q_{xx} < 0$. The output is homogeneous across firms. The aggregate output is the sum of the production from each match. The efficient assignment of workers across firms is the one that maximizes this aggregate output.

Each type-c firm maximizes profits by choosing the skill level x it employs. That is, given c each firm solves the problem

$$\max_x [q(c,x) - w(x)],\tag{2.1}$$

where $w(x)$ is the earnings function. The first-order condition is $w'(x) = q_x(c,x)$. Notice that the magnitude of $w'(x)$ depends on c. This defines a relationship $c(x)$ – the sorting rule – which is discussed below. The second-order condition is $q_{xx}(c,x) - w''(x) < 0$. Differentiating the first-order condition with respect to x yields

$$q_{cx}(c,x)\,\frac{dc}{dx} = w''(c) - q_{xx}(c,x).\tag{2.2}$$

The right-hand side of Equation (2.2) is positive by the second-order condition. Therefore, the left-hand side must also be positive. For $\frac{dc}{dx} > 0$ (i.e., positive sorting) to be the optimal solution, the condition $q_{cx} > 0$ must be satisfied. In other words, to match the best workers with the best firms, we need to assume complementarity between skills and capital. This is consistent with the famous assortative-matching theorem presented by Becker (1973). To capture this, I use the Cobb-Douglas form

$$q(c,x) = c^\eta x^{1-\eta},\tag{2.3}$$

where $\eta > 0$.[3]

Positively assortative matching features a solution in which the top workers are matched with the top firms. To be precise,

$$N_x \int_x^\infty g_x(i)\,di = N_c \int_{c(x)}^\infty g_c(j)\,dj,\tag{2.4}$$

where $N_x > 0$ and $N_c > 0$ are measures of workers and firms, g_x and g_c are the probability densities of workers and firms, respectively. To get a preliminary impression, suppose for the moment that $z\%$ of the workers are

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[3]　I assume constant returns to scale for algebraic simplicity.

above the skill level $\tilde{x}$. Positive sorting implies that $z\%$ of the firms must have productivity greater than $c(\tilde{x})$. Following Sattinger (1979), and for practical purposes that will soon become obvious, I assume that both workers and firms are Pareto distributed with densities

$$g_x(x) = (\gamma_x - 1)x^{-\gamma_x} \quad \text{and} \quad g_c(c) = (\gamma_c - 1)c^{-\gamma_c}, \tag{2.5}$$

respectively, where $\gamma_x > 2$ and $\gamma_c > 2$ (to ensure finite variances). Empirical and theoretical justifications to use Pareto distributions to represent the distributions of worker skills and firm productivity are provided by Simon and Bonini (1958), Adelman (1958), Axtell (2001), Luttmer (2007), Helpman, Itskhoki, and Redding (2010), and Tumen (2011). Lower γ_k, $k \in \{c, x\}$, means that the dispersion of the distribution and, therefore, the inequality is higher. Solving out the sorting equation (2.4) using these densities gives

$$c(x) = \theta^{\frac{1}{\gamma_c-1}}x^{\frac{\gamma_x-1}{\gamma_c-1}}, \tag{2.6}$$

where $\theta = N_c/N_x$. I assume $\theta \in (0,1)$, which means that the number of workers is always greater than the number of firms. The sorting rule (2.6) defines a relationship between c and x. Obviously, $c'(x) > 0$. How fast c increases with x depends on the number of firms relative to the number of workers, and the distributional properties of workers and firms.

A positive reservation value, w_r, arises in this problem, since all firms operate, and there are some unemployed workers due to $\theta \in (0,1)$. If x^* is the skill level of the marginal worker, then the competitive labor market forces would require that $w(x^*) = w_r$.

When the assumed functional forms and the sorting rule (2.6) are plugged into the first-order condition, three objects are pinned down: the earnings function, the reservation value, and the distribution of earnings. Below I provide formulas for these three objects.[4] The first object, the earnings function, is

$$w(x) = \frac{(1-\eta)\theta^{\frac{\eta}{\gamma_c-1}}}{1+\varphi}x^{1+\varphi} + w_r, \tag{2.7}$$

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[4] To focus on the contribution of the paper, I directly give the final formulas, which I have derived by closely following the steps in Sattinger's model. These calculations are well known and are made explicit in Sattinger (1979, 1993) and Tumen (2011).

where

$$\varphi = \eta \frac{\gamma_x - \gamma_c}{\gamma_c - 1} \tag{2.8}$$

characterizes the shape and the curvature of the earnings function. When skills are less dispersed than capital, i.e., $\gamma_x - \gamma_c > 0$, the earnings function is convex in skills $(\varphi > 0)$ and is concave otherwise.[5] In other words, when there are more firms than workers on the right tail, the high demand for top skills produces convexity. On the other hand, when there are more workers than firms on the right tail, i.e., $\gamma_x - \gamma_c < 0$, the higher supply of top-quality workers generates concavity. In what follows, I will assume that the earnings function is convex in skills. The CEO-pay literature documents that small changes in skills result in large compensating differentials at the top of the earnings distribution [see Gabaix and Landier (2008) and Tervio (2008)].[6] Moreover, Piketty and Saez (2003) find that the top earners have experienced enormous gains over the last three decades. These two insights justify the convexity assumption.

The second object, the reservation value, is

$$w_r = \left(\frac{1-\eta}{1+\varphi}\right)\theta^{\frac{\eta}{\gamma_c - 1} + \frac{1+\varphi}{1-\gamma_x}}. \tag{2.9}$$

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[5] Note that Equation (2.7) is derived under the assumption of constant returns to scale (CRS) technology. Deviating from this assumption does not change the principles of the solution we develop, but it does change the results qualitatively. To demonstrate this point, let $\eta > 0$ denote the capital share and $\chi > 0$ denote the labor share in the production technology. With CRS, $\chi = 1 - \eta$. Let's say that we deviate from this assumption and raise χ arbitrarily, which means that $\eta + \chi \geq 1$. A convex earnings function implies that there are more firms on the right tail than workers. Deviating from the CRS assumption by increasing the importance of skills will reinforce the degree of convexity in this example. Similarly, the case $\eta + \chi < 1$, with decreased χ, would weaken the degree of convexity. Analogous arguments can be developed for the effect of η.

[6] Measurement of x poses a challenge to the empirical implementation of the assignment model. But it is possible to develop methods that allow for the derivation of an empirical distribution resembling the underlying ability distribution. For example, Tervio (2008) uses an assignment model to study the determinants of CEO pay. He uses the contribution that CEOs make to total economic surplus, compared to that of their theoretical lowest-type replacements in the sample. He argues that the underlying ability distribution can be inferred from the joint distribution of CEO pay and market value.

Finally, the probability distribution of earnings in this economy is

$$f(w) = \frac{\gamma_x - 1}{1 + \varphi} \left[\frac{1 - \eta}{\frac{\eta}{(1+\varphi)\theta^{1-\gamma_c}}} \right]^{\frac{\gamma_x - 1}{1+\varphi}} (w - w_r)^{-\left(1 + \frac{\gamma_x - 1}{1+\varphi}\right)}. \qquad (2.10)$$

Notice that, due to the Pareto assumptions for the distributions of skills and productivities, the earnings distribution is also of the Pareto form $f(w) = (\gamma_w - 1)\lambda^{\gamma_w - 1} w^{-\gamma_w}$, where the scale parameter is

$$\lambda = \frac{1 - \eta}{\frac{\eta}{(1+\varphi)\theta^{1-\gamma_c}}} \qquad (2.11)$$

and the shape parameter is

$$\gamma_w = 1 + \frac{\gamma_x - 1}{1+\varphi}. \qquad (2.12)$$

The shape and scale parameters of the earnings distribution are functions of the (structural) parameters, and, as a result, earnings inequality changes when these parameters are altered. The proposition presented in the next section builds on this phenomenon.

3. Lorenz Curve and the Gini Coefficient

The Lorenz curve and the Gini coefficient are naturally associated with the Pareto distribution. Let F be the Pareto cumulative density of earnings. Applying the general formulation [see Aaberge (2007) and Cowell (2009)], the Lorenz curve, denoted with L, is

$$L(F) = 1 - (1 - F)^{1 - \frac{1}{\gamma_w}}, \qquad (3.1)$$

and the Gini coefficient, $0 \le G \le 1$, is

$$G = 1 - 2 \int_0^1 L(F) dF = \frac{1}{2(\gamma_w - 1) - 1}. \qquad (3.2)$$

Clearly, the Gini coefficient is an increasing function of the earnings dispersion. Earnings dispersion is a function of three objects: dispersion of skills

(γ_x), dispersion of capital (γ_c), and the share parameter (η). The effects of these three parameters on G can be analyzed separately.[7]

Proposition 1:

G increases when

(i) skills become more dispersed, i.e., γ_x decreases;

(ii) capital becomes more dispersed, i.e., γ_c decreases; and

(iii) labor share increases, i.e., η decreases.

Proof: Differentiating Equation (3.2) only with respect to G and γ_x (taking into account that γ_x affects γ_w and φ), I obtain the following expression:

$$\frac{dG}{d\gamma_x} = -\frac{2}{G^2}\left[\frac{1}{1+\varphi} - \frac{\gamma_x-1}{(1+\varphi)^2}\frac{\eta}{\gamma_c-1}\right].$$

I need to show that $\frac{dG}{d\gamma_x} < 0$. The question is whether the term in brackets on the RHS is positive or negative. Simple algebra yields

$$1 \underset{<}{\overset{>}{\gtrless}} \frac{\gamma_x-1}{1+\varphi}\frac{\eta}{\gamma_c-1} \Rightarrow 1 \underset{<}{\overset{>}{\gtrless}} \eta.$$

Thus, everything comes down to whether η is less than or greater than 1. It is less than 1 obviously, which directly implies that $\frac{dG}{d\gamma_x} < 0$. This completes part **(i)**. For part **(ii)**, I get

$$\frac{dG}{d\gamma_c} = -\frac{2\eta}{G^2}\frac{\gamma_x-1}{(1+\varphi)^2}\left[\frac{1}{\gamma_c-1} - \frac{\gamma_x-\gamma_c}{(\gamma_c-1)^2}\right].$$

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[7] This result is not specific to the Pareto assumption. It can be extended to alternative settings. For example, the log-normal distribution, which fits into the assignment model [Sattinger (1993)], also has a Lorenz curve counterpart. If $\sigma_c > 0$ and $\sigma_x > 0$ are the standard deviations of the (log-normal) distributions of capital and skills, respectively, then the earnings equation in this setting – the counterpart of Equation (2.7) – can be formulated as $w(x) = C\, x^{\frac{\eta\sigma_c+(1-\eta)\sigma_x}{\sigma_x}} + w_r$, where C is a positive constant. Obviously, earnings $(w - w_r)$ will be log-normally distributed. It is well-known that the log-normal distribution also has a closed-form Lorenz curve counterpart [see Cowell (2009)]. Other functional forms are also possible. But the Pareto and log-normal distributions are the most frequently used distributions in the study of inequality.

The sign of $\frac{dG}{d\gamma_c}$ would be positive if the expression in brackets on the RHS were negative. This would be possible only if $\gamma_x < \gamma_c$, which is ruled out by the convexity assumption. This completes part **(ii)**. For part **(iii)**, I get:

$$\frac{dG}{d\eta} = -\frac{2}{G^2}\frac{\gamma_x-1}{(1+\varphi)^2}\frac{\gamma_x-\gamma_c}{\gamma_c-1} < 0,$$

as required. ∎

Part **(i)** says that as the skills dispersion grows, firms start having access to a larger set of skilled workers. This enlarges the earnings horizon, and earnings inequality then widens. This is consistent with the stylized fact that, over the last few decades, American society has faced a dichotomy in schooling achievement as the high-school graduation rate has fallen (after correcting for the GED holders) while college enrollment among high-school graduates has risen. This points to a higher dispersion of skills in the society [Heckman and Masterov (2007)]. In part **(ii)**, given the distribution of skills, a rise in the dispersion of productive capital makes the skilled workers scarce relative to the number of highly productive businesses. The incremental cost of buying an extra unit of skill becomes more expensive. Therefore, earnings inequality climbs. This story is in line with the skill-biased technical-change hypothesis in that a steady movement upward in the demand for skills has contributed to greater earnings inequality. In part **(iii)**, the marginal product of labor goes up in tandem with the labor share. Under convexity, buying one more unit of skill becomes costlier, and inequality surges.

This analysis is useful because it provides an important source of identification. The Gini coefficient has already been calculated in many studies.[8] The earnings-inequality literature estimates the degree of inequality using data on the demand and supply of skills. The approach developed in this paper opens up a new research direction in the study of earnings inequality. Using this model, one can input the Gini coefficient and answer various questions related to sorting (i.e., the sign and the strength of sorting) as well as the sources of inequality (i.e., whether the evolution of the distribution of skills or of the distribution of productivities drives the changes in inequality). Next, we summarize the data regarding the evolution of earnings inequality and its underlying factors in the United States.

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[8] For example, for the United States, see Kopczuk, Saez, and Song (2010) and calculations by the United States Census Bureau. Gini coefficient estimates are available for many countries.

4. Data and Empirical Implications

In this section, I summarize the findings in the relevant literatures regarding the recent trends in the Gini coefficient and the three variables – γ_x, γ_c, and η – that I analyze in Proposition 1. To ensure integrity of the discussion, I focus on the case of the United States.

Figure 1. Gini Coefficient – Trends in US Earnings Inequality
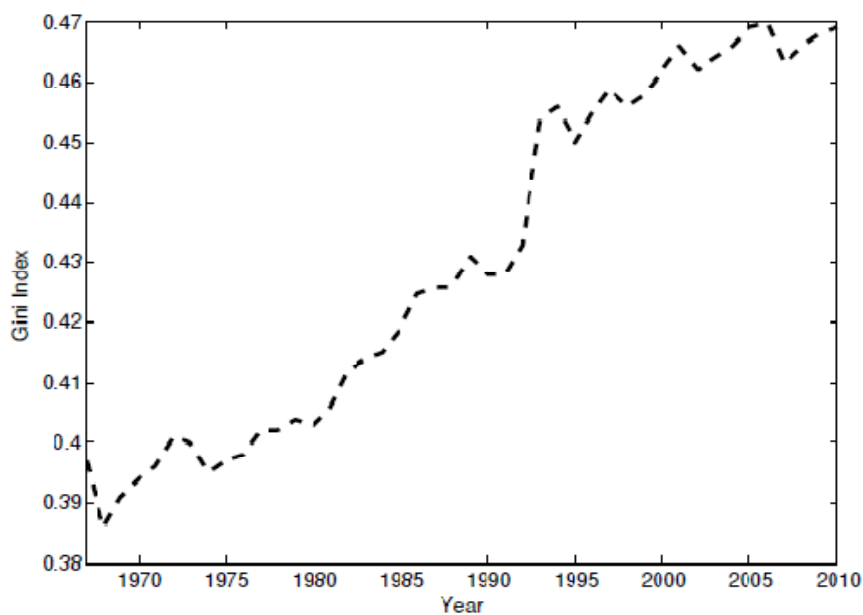
Source: United States Census Bureau

The earnings inequality in the United States has displayed a significant upward trend over the last 40 years. Figure (1) plots the time-series evolution of the annual Gini coefficient estimates (from 1967 to 2010) provided by the United States Census Bureau. There is a striking and steady increase in earnings inequality as the Gini coefficient rises from 0.39 in 1967 to around 0.47 in 2010. Proposition 1 shows that, within the framework of the assignment model, such a rise in the Gini coefficient can originate from three sources: an increase in the dispersion of worker skills, an increase in the distribution of firm productivities, and an increase in labor share.

Figure 2. Dispersion of Skills – Trends in the Educational Composition of the US Workforce
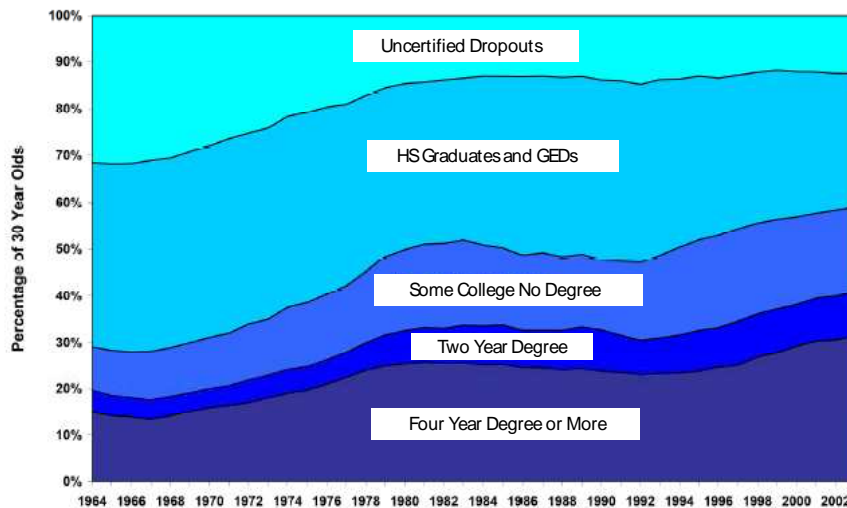
Source: Heckman and Masterov (2007).

Figure (2) summarizes the trends in the educational composition of the US workforce using the CPS data. Clearly, the fraction of college- (and above) educated workers has risen relative to the fraction of high-school- (and below) educated workers. The figure makes clear a distinct acceleration in the dispersion of education in the workforce (under the assumption that education resembles skills). According to Proposition 1, Figures (1) and (2) are consistent with each other in that earnings inequality is rising parallel to the rise in the dispersion of skills.

Two distinct literatures clearly document that the dispersion of firm productivity has become more pronounced over the last 40 years. First, the SBTC literature argues that technological improvements have boosted firms' productive capacities, which in turn created strong demand for high-skill workers [see, for example, Katz and Murphy (1992)]. Technological progress has led to a greater proportion of highly productive firms, resembling a fatter right tail (and greater dispersion) for the productivity distribution. Second, the literature on decomposing TFP growth into firm-level productivities documents the jump in the dispersion of firm productivities within the US manufacturing sector [Dunne, Foster, Haltiwanger, and Troske (2004)].[9] Overall, these studies show that, consistent with the predictions of Proposition 1, higher disper-

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[9] See Faggio, Salvanes, and Van Reenen (2010) for parallel evidence from the UK data.

sion of firm productivity causes more demand for high-skill workers, which is a major source of the increased earnings inequality.

The model's predictions regarding the link between labor share and earnings inequality are inconsistent with the facts. The model predicts that an increased labor share would contribute to more prevalent earnings inequality. However, empirical evidence supports declining labor productivity, rather than increasing, over the past 30 years in the OECD countries [Azmat, Manning, and Van Reenen (2011) and Glyn (2009)]. But, as Figure (1) clearly documents, earnings inequality has been worsening over this period.[10]

From the perspective of Proposition 1, greater dispersion of both worker skills and firm productivities contributes positively to earnings inequality, while a lower labor share contributes negatively to it. Thus, I conclude that the positive contributions coming from the skills dispersion and the productivity dispersion outweigh the negative effect coming from the labor share.

5. Concluding Remarks

This paper establishes explicit links between three literatures: the assignment literature, the earnings-inequality literature, and the literature on the statistical theory of inequality. I have shown that it is possible to attribute rich economic content to the Lorenz curve and the Gini coefficient. The model reveals that interactions between the dispersion of skills, the distribution of productive capital, and input shares determine the degree of earnings inequality. The major contribution is that these interactions, which uncover the connections between economic forces affecting earnings inequality and statistical measurement of inequality, can be directly observed over the Lorenz curve and the Gini coefficient. This framework can thus be used to identify the factors that contribute to movements in inequality. It also provides a decomposition theory for the sources of economic inequality.

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[10] Note that the convexity assumption is responsible for this result. It is assumed that concavity will result in the prediction that labor share and earnings inequality will move in opposite directions, which is consistent with the facts, but this is at the expense of producing adverse results from other predictions of the model.

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