The Effects of Skill-Biased Technical Change on Income Distributions

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Abstract

This thesis broadly investigates the impacts of skill-biased technical change (SBTC) on income distributions.

In Chapter 1, I develop a SBTC model with an intergenerational framework, where heterogeneously-skilled households make intergenerational transfers that determine the skill outcome of the next generation. By increasing the skill-premium, an SBTC shock increases these transfers, thus improving the probability that children from both high and low-skilled households will become skilled. With diminishing returns on investments, the relative improvement in skill outcomes is larger for children from low-skilled households compared to children from high-skilled households, implying that relative skill mobility also improves.

I test the model's predictions in Chapter 2, using data from Chetty et al. (2014) which show how college attendance rates of children in U.S. commuting zones (CZs) are linked to the rank of their families in the national income distribution. A technology measure is constructed for each CZ using its share of STEM (Science, Technology, Engineering, and Mathematics) workers, which I instrument using a Bartik-type IV to deal with endogeneity concerns. From 2SLS estimations, I find that college attendance rates of children from households in the same income rank improve if households are located in higher technology CZs, with the improvement being larger among lower-ranked households. The findings from Chapters 1 and 2 thus suggest that SBTC can improve both absolute and relative skill mobility.

Chapter 3 examines how the skill-premium from the SBTC model can impact between-group inequality among skilled and unskilled workers. I construct a Gini measure for the SBTC model, and find that if the proportion of skilled workers is more than half, a rising skill-premium can actually reduce between-group inequality if the skill-share is also growing. For empirical validation, I observe trends in the skill-portion, skill-premium and two inequality indices (Gini & Theil) for full-time, full-year workers in the U.S from 1980-2018. With the proportion of college-equivalent workers continually increasing, I find that the relationship between the skill-premium and between-group inequality has changed: from 1980-2005, the relationship was strongly positive, while from 2005 onward, it has become negative. Thus, the skill-premium's impact on between-group inequality is not unidirectional.

For Ilana & Araya

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1.1 Introduction

A large literature examines the role of skill-biased technical change (SBTC) in driving the sharp rise in wage inequality in the U.S. and other OECD countries over the past few decades (see Murphy, Riddell & Romer, 1998; Card & Dinardo, 2002; Goldin & Katz, 2008; Acemoglu & Autor, 2011, among others). For example, Acemoglu and Autor (2011) calculate that the composition-adjusted college premium has increased by 38 log points in the U.S. between 1980 and 2008, meaning that the average earnings of a college graduate have grown 46% relative to the earnings of a high school graduate. This increase has happened in spite of the relative supply of college versus non-college educated workers growing by close to 60% in the same period; consequently, the observed skill premium is linked with an increase in the demand of skilled labour, which in turn is linked to skill-biased technical change under Tinbergen's (1975) assumption. An area which has been left unexamined, however, is how SBTC might have potentially impacted the intergenerational mobility of skills. This question is particularly relevant as studies on intergenerational mobility (Becker & Tomes, 1979, 1986; Solon, 1992, 2004; Chetty, Hendren, Kline & Saez, 2014; Connolly, Corak & Haeck, 2019 etc.) strongly indicate that income levels of parents today can significantly influence the income/education outcomes of their children tomorrow. For example, the well-known work of Chetty et al. (2014) on intergenerational mobility in the United States shows a strong linear relationship between a child's probability of attending college and his/her parent's rank in the national income distribution; on average, a 10 percentile point increase in the parental income rank increases the college attendance rate of the child by 6.7 percentage points. With skill-biased technology widening the income gap between differently-skilled people and increasing the returns to education, one would naturally expect it to influence the ability and intent of parents to invest in the human capital development of their children, thereby impacting intergenerational mobility.

This paper theoretically explores the impact of skill-biased technical change on the intergenerational mobility of skills, using the channel of intergenerational transfers. Given a setting with a heterogeneous skill-distribution (skilled and unskilled workers), I analyze how technical change will impact a household's decision to invest in the human capital development of their children, which determines their future skill type. When I allow for SBTC within this intergenerational framework, I find that skill-biased technical change incentivizes households to increase intergenerational transfers, as the returns from "producing" skilled children are now higher. This improves *absolute skill mobility* across generations of the same family. Moreover, due to diminishing returns in human capital investments, the relative improvement in mobility turns out to be higher for the low-skilled group when transfers get increased, as they initially start from lower investment levels. This improves *relative skill mobility.* If we follow the standard assumption used in empirical studies where being skilled is equated with attending college (Card & DiNardo, 2002), this result implies that SBTC helps in shrinking the gap in college attendance rates between children from rich and poor families.

The starting point of this work is the insight that SBTC can have *intergenerational effects*- i.e. it can motivate changes in social/income status between different generations of the same family. There are two reasons why the existence of such intergenerational effects are plausible. First, it is well documented that parents undertake substantial expenditures to influence their children's development- for example, Haveman and Wolfe (1995) calculate that, after factoring in both direct costs and implicit time costs, the cost of raising a child in the United States in 1995 was $20,000 annually per family (in terms of 2018 dollars, this amount would be around $32,000).[1] By impacting incomes, SBTC can impact the ability of parents to make these investments. Second, the rate of return on schooling is known to have an influence on intergenerational investments in education (Solon, 2004)- by increasing the returns to being skilled, SBTC can impact the intent of parents to invest in the education of their children.

In order to study these intergenerational effects, I incorporate an intergenerational framework, where parents transfer resources to influence the fortunes of their children (e.g. Becker & Tomes, 1979, 1986) within the standard SBTC model (e.g. Bound & Johnson, 1992; Acemoglu, 1998; Autor, Katz & Krueger, 1999). As inherent in SBTC models, the economy has two types of workers, skilled and unskilled, who are working for a firm which uses a CES production function. The innovation is that on the household side, these workers are now considered to be members of infinitely long-lived families, with each generation having one parent worker and one child. The parental agents are altruistic and they invest in the skill development of their children by making intergenerational transfers.

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[1] Parents are typically considered to make a range of expenditures that can influence their children's attainments, such as investments behind their "skills, health, learning, motivation, 'credentials', and many other characteristics" (Becker & Tomes, 1986, p. S5).

Higher transfers increase the probability of making the child skilled, and it is assumed that these investments are subject to diminishing marginal returns but are complementary to parental skill-type (e.g. Becker, Kominers, Murphy & Spenkuch, 2018). SBTC influences these transfers by shaping income levels of parents in the current period and the expected returns to skill in the next period. The interplay between skill-biased technology and intergenerational transfers leads to an endogenous skill-supply within this SBTC model, and the economy is shown to reach a unique and stable steady-state equilibrium.

The impact of skill-biased technical change in the model is then assessed through an exercise in comparative statics. I show that technological change, through its positive impact on the skill premium, incentivizes both skilled and unskilled households to increase their intergenerational transfer levels so that the probability of their offsprings becoming skilled can improve. Moreover, children from unskilled households, who are initially at lower probability levels of becoming skilled, experience larger relative improvements when intergenerational transfers are increased, given the assumption of diminishing returns in human capital investments. The overall increase in intergenerational investments also leads to the economy having a larger fraction of skilled workers, meaning that technical change in the model is found to endogenously increase both the skill premium and the supply of skills.

The central contribution of this work is to bridge the gap between two well-known strands of economic literature. One is the literature on intergenerational mobility, which follows from the viewpoint that the fortunes of children are linked to their parents', as originally established by Becker and Tomes (1970, 1986). Since then, there has been an extensive amount of work on the link between inequality and intergenerational mobility, as reviewed by Solon (1999) and Black and Devereux (2011). The work in this paper adds a new dimension to these analyses, by examining a theoretical link between a well-known *driver* of income inequality- skill-biased technical change- and intergenerational mobility. While previous studies have discussed the link between the rate of return on human capital and intergenerational mobility (e.g. Solon, 1999), the impact of technology on mobility, through its influence on intergenerational investments, has not been directly examined.

The second strand of literature that this paper contributes to is the literature on SBTC itself. An extensive amount of research has taken place to understand the causes of income inequality within societies, with skill-biased technical change being identified as one of the driving forces (reviewed by Card & DiNardo, 2002).[2] The primary focus of these studies

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[2] Other factors associated with changes in the wage-structure (especially in the U.S.) include: changing

has been to note how SBTC has changed incomes between differently skilled people from the same generation; however, whether SBTC could have led to changes in the skill status between different generations of the same family has remained unexamined. The model here finds that SBTC can lead to these intergenerational changes, by improving skill mobility (increasing the probability that the next generation will go to college). As a college education is typically considered to be the main gateway to higher incomes (e.g. Corak, 2013), this would correspondingly lead to improvements in income and social status across generations. To the best of my knowledge, the viewpoint that SBTC can lead to changes in income levels from an intergenerational perspective has not been explored in previous SBTC literature.

The rest of the chapter is organized as follows. Section 1.2 describes the set-up of the theoretical model. In Section 1.3, I show how the aggregate skill-supply in the economy reaches a steady state, leading to steady-state solutions for other key variables in the model. The effect of an SBTC shock on these steady-state solutions are then analyzed in Section 1.4. Section 1.5 concludes the chapter, and mentions possible areas for extending the research.

1.2 Theoretical Framework

I consider an economy in discrete time. The household side has overlapping generations- in every period, each household has one adult parent worker (skilled or unskilled) and one child. Parents are altruistic and care about the future welfare of their children, so they make intergenerational investments in human capital to increase the probability of making their children skilled. The degree of these intergenerational transfers determine the fraction of skilled workers in every period. On the production side, a representative firm uses a CES production function with two labour inputs- skilled and unskilled labour- which are taken to be gross substitutes. The marginal products of labour, which are conditional on the factor-augmenting technology terms and the supply of labour inputs, give the skilled and unskilled wage rates (along with the skill-premium), and these variables feed back to the household's decision making process in every period.

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trade patterns due to globalization which has shifted manufacturing to lower-wage countries (Acemoglu, Autor, Dorn, Hanson & Price, 2016), de-unionization of labour (Acemoglu & Violante, 2001), and fall in the real value of the minimum wage (Teulings, 2003; Acemoglu & Autor, 2011).

1.2.1 Production Side

On the production side, the economy produces a single consumption good under conditions of perfect competition. The consumption good is treated as the numeraire, and the price is normalized to 1 throughout the analysis. Output is produced using a Constant Elasticity of Substitution (CES) production function that uses two type of labour as inputs- skilled and unskilled- represented by H_t and L_t respectively (there is no capital in the model):[3]

$$Y_t = [A_H(H_t)^v + A_L(L_t)^v]^{\frac{1}{v}} \tag{1.1}$$

where $v \equiv (\sigma - 1)/\sigma$, with σ being the elasticity of substitution between the two labour inputs. Gross substitutability between the two labour inputs requires $\sigma > 1$, which implies that $v \in (0, 1]$.[4] The factor-augmenting technology terms for the skilled and unskilled labour inputs are A_H and A_L respectively, and these are treated as exogenous in the model. Any improvement in skill-biased technology is captured by an increase in (A_H/A_L).

The wage rates for each worker type are found from the marginal products of skilled and unskilled labour. The ratio between the skilled wage and unskilled wage then gives the skill-premium (wage gap) in the model, ω:[5]

$$\frac{w_{H,t}}{w_{L,t}} = \omega_t = \left(\frac{A_H}{A_L}\right)\left(\frac{L_t}{H_t}\right)^{1-v} \tag{1.2}$$

Equation (1.2) is the standard returns to skill equation in the SBTC model. It shows that, with gross substitutability between the two inputs, the wage gap is increasing in the ratio of A_H/A_L, i.e. when the factor-augmenting technology term for the skilled worker is growing faster than the technology for the non-skilled worker. Conversely, the wage gap is falling in the ratio of H/L, which captures the relative supply of skills.[6]

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[3] For empirical applications, the standard approach is that H can be taken to represent the number of college graduates (or college equivalent workers), while L can represent the number of high school graduates (or high school equivalent workers) in the work force. See Card and DiNardo (2002).

[4] The assumption of labour inputs being gross substitutes is standard in major works using the SBTC model, such as by Acemoglu (1998), Card and DiNardo (2002), Acemoglu and Autor (2008, 2012), among others. This is also supported empirically- one estimate for the elasticity parameter, σ, provided by Autor, Katz, and Krueger (1998) is around 1.5, when the two skill groups considered are college-equivalent and high-school equivalent workers. This would imply that the corresponding value of v is 0.33.

[5] The terms *skill premium* and *wage gap* are used interchangeably throughout the paper to refer to the relative returns of being a skilled worker.

[6] For a detailed discussion of the comparative statics from the SBTC model, see Acemoglu and Autor

1.2.2 Household Side

On the consumer side of the economy, at any given period t, a household is composed of two agents: a parent/adult and a child. The adult agent is either *skilled* or *unskilled*, denoted by sub-script $j \in \{H,\ L\}$, with the skill-type being determined by parental investments in human capital that took place in period $(t-1)$ through a process that is described in detail below.[7] All adult agents are endowed with 1 unit of time; they allocate $u_{j,t}$ portion to work earning their corresponding wage level (w_H or w_L). A standard assumption followed is that skilled workers can choose whether to work as skilled or unskilled employees, implying that the skilled wage can never fall below the unskilled wage (e.g. Mokherjee & Napel, 2006).

At time t, the fraction of skilled workers in the economy is denoted as h_t and the portion of unskilled workers is correspondingly $(1-h_t)$. The distribution of h at the onset of the economy is exogenously determined (i.e. h_0 is known).

1.2.3 Intergenerational Investments

Adult agents are altruistic and care about the future skill-state of their child. A standard assumption of intergenerational models is that due to imperfect capital markets (Galor & Zeira, 1993), parents cannot borrow against their descendant's future income, but have to invest their own resources for their children's skill development. The traditional approach is to model these investments as either a capital-investment input (i.e. the amount of monetary resources being invested in children, e.g. Solon, 2004), or a time-input (i.e. the amount of time spent teaching one's own children, e.g. Moav, 2005), or both (e.g. Fan & Zheng, 2012). In the context of the SBTC environment, it is meaningful to use an intergenerational transfer set-up which incorporates both the time and capital inputs, as technical change can impact these two types of expenditures differently. On the one hand, by increasing productivity and incomes, it can make it easier for agents to undertake the direct investments which are typically market-purchased. On the other, it can also make time-investments in child-care more costly, as the opportunity cost of work increases with rising wages.

(2011).

[7] In other words, an agent receives human capital investments in the *child* stage of his/her life. During the *adult* stage, each agent forms their own household and immediately gives birth to one child, while his/her former household disappears. Thus, there is no population growth in the model.

I account for the time-investment input by considering it is the amount of time which the adult agent is not working, but spending at home with the child, i.e. $(1 - u_{j,t})$. I account for the capital-investment input by considering that it is the portion of total income, $w_{j,t}u_{j,t}$, which the adult agent decides to invest in the child; this is denoted as $k_{j,t}$.[8]

A third potential channel which becomes relevant in the SBTC framework is skill complementarity, as educated parents are generally found to be more productive at teaching their children (see Lareau, 2011; Heckman & Mosso, 2014; Becker et al., 2018, among others). A standard way to model this is to make use of an *effectiveness parameter* (denoted here as a_j) which can capture the level of productivity of parents in the skill-development process of their children.[9]

Based on the intergenerational investments, the probability that a child from household j will become skilled as an adult is given by the following function:

$$p_{j,t} = a_j \left[1 - \frac{u_{j,t}^{\gamma}}{k_{j,t}^{\theta}} \right] \tag{1.3}$$

This probability function satisfied the following conditions:

1. The probability of becoming skilled is increasing in the capital-investment input, k, but with diminishing returns, i.e. $p_k > 0$, $p_{kk} < 0$. This requires that the exponent $\theta \in (0, 1)$.

2. The probability of becoming skilled is decreasing in u (the portion of time worked), as work takes away time from child rearing, i.e. $p_u < 0$. While more time spent in child-rearing increases the probability that the child will get skilled, the marginal returns are high from the initial time allocated to this task, and then gradually diminishes, i.e. $p_{uu} < 0$. This requires that the exponent $\gamma \geq 1$.

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[8] Analogously, one can also think of k as being a kind of bequest. This inheritance can then be invested by the children in their education during the adult period of their lives. Intergenerational models with the bequest motive were pioneered by Barro (1974), Loury (1981), Davies (1982), and Galor and Zeira (1993).

[9] An example of the use of this effectiveness parameter in intergenerational models comes from Fan and Zheng (2012). They use a production function for human capital which is in the following Cobb-Douglas form: $e = \gamma_i k^{\delta} d^{1-\delta}$, where e is the education level of this child, d is education expenditure, k is parental time input and γ is the effectiveness parameter. They assume that γ varies across individuals, with skilled parents having a higher value of γ than unskilled ones.

3. The *effectiveness parameter* is set so that $a_H > a_L$ and $a_j \in (0, 1]$ (given the range of the probability function).
4. There is imperfect substitutability between the time-input and capital-input in the skill-development process: if parents cut down on one input, they would need to make more investments in the other input to compensate.[10] This is visually demonstrated in Figure 1, which depicts an isoquant map constructed from equation (1.3).

1.2.4 Budget Constraint

Factoring in the intergenerational investments, the budget constraint for an adult agent of type j at time t can be written as:

$$w_{j,t}u_{j,t} = c_{j,t} + k_{j,t} \tag{1.4}$$

where $w_{j,t}u_{j,t}$ is total adult income, $k_{j,t}$ is the amount of income invested in the child, and $c_{j,t}$ is the amount of income spent for own consumption (with $c_{j,t} > 0$, $k_{j,t} > 0$).

1.2.5 Preferences

Following Becker and Tomes (1979), I assume that parental preferences are a function of their own consumption, and the welfare of their immediate offsprings (this rules out the need for a parent to form beliefs about his/her dynasty welfare beyond $t + 1$). In the model here, the future welfare of the child is conditional on the skill-state they achieve. However, note that unskilled is a default state in the model that does not need any parental investments (e.g. Mokherjee and Napel, 2006). This has two important implications.

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[10] Evidence for this comes from Guryan, Hurst and Kearney's (2008) work on the link between parental education and parental time use at home from American Time Use Surveys. They find that, while mothers reduce the amount of time allocated to home production activities (such as household chores) when their education levels rise, the opposite holds true for child-care activities. They theorize this is explained by the difference in the *degree of substitutability* between the market-input and the time-input when it comes to producing different commodities at home. For usual home-production activities (like cooking, cleaning etc.), there is a fair degree of substitutability between the time and market inputs; this leads to parents reducing their time input in these activities as their incomes rise. However, in the case of child-care, the evidence suggests that parents view market-purchased child-care options as weaker substitutes for parental time; thus, parents prefer not to cut back on time spent in child-care even if they can afford the market-based alternative.

First, it means that parents should not get any utility if the child becomes unskilled after intergenerational transfers have been made. Second, it implies that parents should care more about the relative returns of being skilled, rather than absolute returns.[11] As the relative returns from being skilled (tomorrow) is given by the future wage-gap, it can be considered that the utility value from having a skilled child is proportional to ω_{t+1}. This formulation captures the fundamental notion that forward-looking parents care about the returns to education, and the higher the relative difference in earnings between the skilled and unskilled state, the more the incentive to invest in human capital development.[12]

Following this exposition, the preferences of the adult agents in time t are assumed to be given by:

$$U_{j,t} = ln(c_{j,t}) + \beta[p_{j,t}\omega_{t+1}] \tag{1.5}$$

In Equation (1.5), $c_{j,t}$ is the consumption level of the adult agent in the current period; $p_{j,t}$ is the probability that the child will become skilled from the intergenerational investments; ω_{t+1} is the future wage-gap, which represents the relative value from the high-skilled state being realized by the child in $(t+1)$; β is the usual discount factor, with $\beta \in (0,1)$.

An important note about the formulation of preferences is that it is based on wages being non-stochastic in the model. While at the individual level the skill-outcome is probabilistic, at the aggregate level, the total number of agents becoming skilled and unskilled in the economy is known by the law of large numbers. This makes the marginal products to each type of labour (and the wages) known, and the (future) wage gap can be rationally predicted.

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[11] Using a simple example, it can be seen why relative returns would be more important than absolute returns, if unskilled is a default outcome. Consider two scenarios: in scenario A, the wage for the skilled worker (w_H) is 100, and the wage for the unskilled worker (w_L) is 99; in scenario B, $w_H = 6$ and $w_L = 3$. While absolute incomes are higher in scenario A, the incentive to invest in education is lower; even with zero investments, a person can earn the default (unskilled) wage of 99 which is close to the skilled wage of 100. In scenario B, absolute incomes are lower, but being skilled can make the person twice as well off compared to being unskilled. Thus, the incentive to invest in education should be rationally higher.

[12] This assumption also appears to have empirical validity- for example, one of the reasons for the slowdown of the relative supply of college educated workers in the U.S. in the 1980s is said to be the sharp decline of the college premium in the earlier decade, which discouraged high school graduates from investing in a college education (Card & Lemieux, 2001).

1.2.6 Optimization

The problem of an adult agent of type j maximizing utility in Equation (1.5) subject to the budget constraint in (1.4) and the probability function in (1.3) can be expressed as:

$$max\left\{ln(w_{j,t}u_{j,t}-k_{j,t})+\beta\left(a_j\left[1-\frac{u_{j,t}^{\gamma}}{k_{j,t}^{\theta}}\right]\omega_{t+1}\right)\right\} \tag{1.6}$$

where the agent chooses $u_{j,t}$ and $k_{j,t}$, taking $w_{j,t}$ and ω_{t+1} as given. The optimal solutions from the maximization problem are:

$$u_{j,t}=\left[\frac{(\theta w_{j,t})^{\theta}}{a_j\beta\omega_{t+1}(\gamma-\theta)\gamma^{\theta}}\right]^{\frac{1}{\gamma-\theta}} \tag{1.7}$$

$$k_{j,t}=\frac{\theta w_{j,t}u_{j,t}}{\gamma} \tag{1.8}$$

Equations (1.7) and (1.8) respectively give the equilibrium choices of time spent working by the adult agent (the time spent for child-care is correspondingly $(1-u_{j,t})$) and the value of capital investment in the child. Certain conditions on the parameters ensure that there is an interior solution to the optimization problem (i.e. $0 < u_{j,t} < 1$, which also means that $k_t > 0$); these conditions are discussed in Appendix A1.

Plugging in the solutions of $u_{j,t}$ and $k_{j,t}$ in the probability function defined in Equation (1.3) yields:

$$p_{H,t}=a_H-\left[\frac{1}{\beta\omega_{t+1}(\gamma-\theta)}\right] \tag{1.9}$$

$$p_{L,t}=a_L-\left[\frac{1}{\beta\omega_{t+1}(\gamma-\theta)}\right] \tag{1.10}$$

Equations (1.9) and (1.10) represent the measures of the intergenerational mobility of skills in the model.[13] Specifically, $p_{H,t}$ is the probability with which children belonging to

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[13] It can be noted here that the conditions on the parameters which ensure an interior solution to the optimization problem (as discussed in Appendix A1) also ensure that $p_{j,t}\in(0,1]$.

skilled households of generation t will become skilled in $(t+1)$, while $p_{L,t}$ is the probability with which children belonging to unskilled households of generation t will become skilled in $(t+1)$. Hence, these measures capture within-group mobility, or *absolute skill mobility.* Additionally, a measure of *relative skill mobility* can be derived in the form of an odds ratio (Iyigun, 1999; Fan & Zheng, 2012)- the relative odds of being skilled for the children of unskilled parents compared with the children of skilled parents:

$$\rho_t \equiv \frac{p_{L,t}}{p_{H,t}} = \frac{a_L \beta(\gamma - \theta)\omega_{t+1} - 1}{a_H \beta(\gamma - \theta)\omega_{t+1} - 1} \tag{1.11}$$

The solutions of $p_{j,t}$ show that, given the earlier assumption about $a_H > a_L$, it must be the case that $p_{H,t} > p_{L,t}$ (which implies $\rho_t < 1$). That is, in equilibrium, children from skilled households turn out to have a higher probability of becoming skilled compared to children from unskilled households, and this difference in the model is solely caused by skill complementarity.[14]

The absolute intergenerational mobility measures are also found to be increasing in the future wage-gap, ω_{t+1}. The higher the future returns to skill, the more the incentive for parents (of both skill types) to invest in the skill development of their child, which will increase the probability that their child becomes skilled. Also, as the absolute measure is lower for the unskilled households, the relative change in $p_{L,t}$ is higher than the relative change in $p_{H,t}$ for a given increase in ω_{t+1}; consequently, the odds ratio is also increasing in the future wage-gap.

1.3 Evolution of Aggregate Skill-Supply

The law of motion for the fraction of skilled workers in the economy is given by:

$$\phi(h_t) \equiv h_{t+1} = h_t p_{H,t} + (1 - h_t) p_{L.t} \tag{1.12}$$

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[14] A similar result is found in a theoretical work done by Becker et al. (2018), who show that the persistence of economic status can be explained by skill complementarity. Specifically, their model assesses intergenerational mobility by using a measure of intergenerational income elasticity derived in the steady-state; higher elasticity implies lower mobility since it means the parent's and offspring's income is strongly correlated. They show that the elasticity measure is an increasing function of the parent's productivity parameter in their children's human capital investment, which leads to higher persistence of economic status at the top of the income distribution.

where $p_{H,t}$ and $p_{L,t}$ have been specified in Equations (1.9) and (1.10).

Note that the only endogenous variable in these probability equations is the future wage-gap, ω_{t+1}, which can be replaced by updating the original wage-gap equation in (1.2) by one period. Using the labour-market clearing conditions, $H_t = u_{H,t}h_t$ and $L_t = u_{L,t}(1-h_t)$, the wage gap equation is first re-written as:

$$\omega_t = \left[\left(\frac{A_H}{A_L}\right) \left(\frac{1-h_t}{h_t}\right)^{1-v} \left(\frac{a_H}{a_L}\right)^{\frac{1-v}{\gamma-\theta}} \right]^{\frac{\gamma-\theta}{\gamma-\theta v}} \tag{1.13}$$

Updating Equation (1.13) by one period gives the expression for ω_{t+1}. This is substituted in the probability functions to find:

$$p_{j,t} = a_j - \left(\frac{1}{\beta(\gamma-\theta)}\right) \left[\left(\frac{A_L}{A_H}\right) \left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{1-v} \left(\frac{a_L}{a_H}\right)^{\frac{1-v}{\gamma-\theta}} \right]^{\frac{\gamma-\theta}{\gamma-\theta v}} \tag{1.14}$$

The final step is substituting Equation (1.14) into the initially specified law of motion, to get:

$$h_{t+1} + \left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{\frac{(1-v)(\gamma-\theta)}{\gamma-\theta v}} \left(\frac{1}{\beta(\gamma-\theta)}\right) \left[\left(\frac{A_L}{A_H}\right) \left(\frac{a_L}{a_H}\right)^{\frac{1-v}{\gamma-\theta}} \right]^{\frac{\gamma-\theta}{\gamma-\theta v}} = h_t(a_H - a_L) + a_L \tag{1.15}$$

Equation (1.15) implicitly determines h_{t+1} as a function of h_t and the exogenous parameters of the model.

1.3.1 Steady-State Solution for Fraction of Skilled Workers

I now proceed to show that the fraction of skilled workers in the economy will evolve to a steady-state solution under constant technology, which will also lead to steady-state solutions for the the other key variables in the model.

The law of motion equation in (1.15) implies the following:

Lemma 1 *the law of motion equation is a continuous, increasing function which intersects the 45-degree line at an unique point. This implies that the portion of skilled workers in the economy converges to a steady-state solution, h^*, which is globally stable.*

Proof:

For convenience with notation, I re-write the law of motion equation (from 1.15) as:

$$h_{t+1} + D\left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{x} = h_t(a_H - a_L) + a_L \tag{1.16}$$

where:

1. $D \equiv \left(\frac{1}{\beta(\gamma-\theta)}\right)\left[\left(\frac{A_L}{A_H}\right)\left(\frac{a_L}{a_H}\right)^{\frac{1-v}{\gamma-\theta}}\right]^{\frac{\gamma-\theta}{\gamma-\theta v}}$, where $D > 0$.
2. $x \equiv \frac{(1-v)(\gamma-\theta)}{\gamma-\theta v}$, where $0 < x < 1$. These boundary conditions arise as $\gamma > \theta$ and $v < 1$. Thus, it must always be the case that $(\gamma - \theta v) > (1-v)(\gamma-\theta)$, i.e. the denominator is larger than the numerator, leading to x being a fraction value.

Equation (1.16) is specified in the form of $h_{t+1} = \phi(h_t)$. Using implicit differentiation, the first and second order derivatives of $\phi(h_t)$ are found to be:

$$\frac{\partial h_{t+1}}{\partial h_t} = \frac{(a_H - a_L)}{\left[1 + Dx\left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{x-1}\left(\frac{1}{(1-h_{t+1})^2}\right)\right]} \tag{1.17}$$

$$\frac{\partial^2 h_{t+1}}{\partial h_t^2} = -\frac{Dx(a_H - a_L)\left(\frac{1}{(1-h_{t+1})^3}\right)\left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{x-1}\frac{\partial h_{t+1}}{\partial h_t}\left[2 - \left(\frac{1-x}{h_{t+1}}\right)\right]}{\left[1 + Dx\left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{x-1}\left(\frac{1}{(1-h_{t+1})^2}\right)\right]^2} \tag{1.18}$$

The first order derivative of the transition function is positive and always non-zero, which implies $\phi(h_t)$ is a continuous, increasing function. Moreover, the numerator is always smaller than the denominator in the first-order derivative calculated (as $a_H > a_L$ and $\{a_H, a_L\} \in (0,1]$). Consequently, it must be the case that $\phi'(h_t) \in (0,1)$.

The sign of the second order derivative is conditional on the term: $2-\left(\frac{1-x}{h_{t+1}}\right)$. If $2-\left(\frac{1-x}{h_{t+1}}\right)>0$, then the function is concave; otherwise, convex.[15]

Calculating the value of the function at $h_t=0$ and $h_t=1$:

$$\phi(0) \Rightarrow \quad h_{t+1}+D\left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{x}=a_L \tag{1.19}$$

$$\phi(1) \Rightarrow \quad h_{t+1}+D\left(\frac{h_{t+1}}{1-h_{t+1}}\right)^{x}=a_H \tag{1.20}$$

Given that $1 \geq a_H > a_L > 0$, the starting point of the function must be above the 45-degree line, while it must finish below (or at maximum on) the 45-degree line. Consequently, the transition function (irrespective of being concave or convex) must intersect the 45-degree at an unique point, which is the steady-state value of the system, h^*.

Also, from Equation (1.17), the value of $\phi'(h^*)\in(0,1)$, which means that h^* is globally stable.□

Intuitively, the reason for the stock of skilled of workers in the economy to reach steady-state is as follows. Consider that the initial stock of h is low; for a given level of the skill-biased technology factor then, the wage gap will be relatively high. This incentivizes parental agents to optimally transfer resources to their childs, so they have a high probability of becoming skilled. What follows is a large increase in the supply of skills for the next period, but the skill-premium is reduced since technology has stayed constant. Parental agents now adjust their intergenerational transfers, and the growth in the supply of skilled workers slows down. This process happens recursively until the portion of the skilled workers in the economy reaches steady-state. This also leads to steady-state solutions for the individual wages (w_j^*), the wage gap (ω_j^*), the input choices (u_j^*, k_j^*), the probability measures (p_j^*), and the odds-ratio (ρ_j^*).

This evolution of h to steady-state is visually demonstrated in Figures 2 and 3. The simulations have been done with $h_0=0.05$, $A_H/A_L=2$, $a_H=1$, $a_L=0.5$, $\gamma=2$, $\theta=0.5$, $\beta=0.98$ and $\upsilon=0.33$.

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[15] Note that the second derivative in (1.18) can be zero if $2=\left(\frac{1-x}{h_{t+1}}\right)$, which raises the possibility of an inflection point (and multiple equilibria). However, as the first derivative is always less than 1, the transition function cannot cut the 45-degree line at two points inside the domain- thus, there has to be an unique steady-state solution.

1.4 Comparative Statics: Impact of SBTC

The impact of technical change in the model is now analyzed through an exercise in comparative statics, by looking at how a change in (A_H/A_L) will affect the steady-state solutions of h^*, ω^*, p_j^*, and ρ^*. The results that follow can thus be interpreted as how the economy will change if there is a discovery/invention that leads to a one-time change in the technology level; equivalently, it can also be considered that steady-state solutions are being compared across two economies, one in which the A_H level is higher than the other.

1.4.1 Effect on Fraction of Skilled Workers

The steady-state value of h^* is given by the equation:

$$h^* \left(1 - (a_h - a_l)\right) = a_L - D\left(\frac{h^*}{1-h^*}\right)^x \tag{1.21}$$

where the complete forms of D and x have been specified earlier.

To find out how an increase in A_H will impact h^*, I will consider the LHS and the RHS of Equation (1.21) as two different functions, $f(h)$ and $g(h)$ (dropping the $*star$ notation for now):

$$LHS: \quad f(h) = h\left(1 - (a_h - a_l)\right) \tag{1.22}$$

$$RHS: \quad g(h) = a_L - D\left(\frac{h}{1-h}\right)^x \tag{1.23}$$

The function, $f(h)$ which represents the LHS is a straight line with a positive slope, $(1 - (a_h - a_l)) < 1$. Its value is zero when $h = 0$, which means it starts from the origin and slopes upwards.

The value of the function $g(h)$ is a_L when $h = 0$, and this value diminishes as $h \to 1$. This can be seen from the first derivative of $g(h)$ which is negative:[16]

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[16] The sign of the second-order derivative will not affect the analysis- the same comparative statics results will hold irrespective of whether $g(x)$ is concave or convex.

$$g'(h) = -x\frac{D}{(1-h)^2}\left\{\left(\frac{h}{1-h}\right)^{x-1}\right\} < 0$$

Finally, setting $g(h) = 0$, a corresponding value for h (denoted as $\bar{h}$) can be found which is the point where the function cuts the horizontal axis:

$$\bar{h} = \frac{(\frac{a_L}{D})^{\frac{1}{x}}}{\left[1 + (\frac{a_L}{D})^{\frac{1}{x}}\right]} \tag{1.24}$$

Figure 4 shows how the LHS and the RHS of Equation (1.21) would look like if they were now drawn in the same diagram. The horizontal axis represents the domain of h, while the vertical axis represents the corresponding ranges of the $f(h)$ and $g(h)$ functions. The point of intersection between the the functions $f(h)$ and $g(h)$ is the unique (original) steady state value of $h \equiv h^*$, which satisfies the equation given in (1.21).

The comparative statics problem can now be solved by examining how a change in A_H will impact the $f(h)$ and $g(h)$ equations (and finding out their new point of intersection). First, with respect to the $g(h)$ equation, note that an increase in A_H will reduce the value of the term $D \equiv \left(\frac{1}{\beta(\gamma-\theta)}\right)\left[\left(\frac{A_L}{A_H}\right)\left(\frac{a_L}{a_H}\right)^{\frac{1-v}{\gamma-\theta}}\right]^{\frac{\gamma-\theta}{\gamma-\theta v}}$. When there is a change in D, its corresponding impact on the value of $\bar{h}$ is negative, as seen from the first-order derivative calculated from Equation (1.24):

$$\frac{\partial\bar{h}}{\partial D} = -\frac{a_L\left(\frac{1}{x}\right)D^{-(1/x)-1}}{\left[1 + (\frac{a_L}{D})^{\frac{1}{x}}\right]^2} < 0 \tag{1.25}$$

Thus, it must be the case that: $A_H \uparrow \Rightarrow D \downarrow \Rightarrow \bar{h} \uparrow$, which correspondingly means that the x-axis intercept of the $g(h)$ equation must shift out (depicted as movement from $g(h)^{old}$ to $g(h)^{new}$ in Figure 4). With $f(h)$ unchanged (as $f(h)$ does not include the A_H term), there will now be a new point of intersection between $f(h)$ and $g(h)$, which represents the new steady-state: h^*_{new}. As $h^*_{new} > h^*$, it is concluded that any increase in the skill-biased technological factor must lead to an increase in the portion of skilled workers in the economy in the new steady-state. □

Proposition 1: *An increase in the skill-biased technology factor increases the portion of skilled workers in the SBTC model*

1.4.2 Effect on Skill-Premium

To study the impact on the skill-premium (wage gap), recall that the originally specified law of motion in Equation (1.12) was given as:

$$h_{t+1} = h_t p_{H,t} + (1 - h_t) p_{L.t}$$

Using the steady-state condition, the solution of h^* in terms of p_H^* and p_L^* can be written as:

$$h^* = \frac{p_L^*}{1 - (p_H^* - p_L^*)} \tag{1.26}$$

From Equation (1.26), it is evident that h^* is increasing in both p_H^* and p_L^*, which is an intuitive result- higher investments in skill development at individual levels will increase the probabilities of becoming skilled, leading to a higher portion of skilled workers in the economy. Thus, if an economy is moving from $h_1^* \rightarrow h_2^*$ where h_2^* is higher, this can only happen under the condition that at least one of p_H^* or p_L^* has gone up.

The equations on p_j^* show that the only endogenous variable that can increase the steady state value of p_j^* is the wage-gap, ω^*. This result is again fairly intuitive- only an increase in the returns to skill will incentivize parents to invest more in the skill-development of their future generation, leading to a higher level of h^* in the new steady state. Using these relationships, the second important result of the comparative statics exercise is derived- *an increase in A_H will lead to an increase in h^* if and only if the skill-premium increases.*

Proposition 2: *An increase in the skill-biased technology factor leads to an increase in the skill-premium*

A consequence of Propositions 1 and 2 is that the wage gap which results from technical change in the endogenous model is lower than what would be observed in the standard SBTC model (where the skill-supply does not change with changes in the technology level). This can be seen from a simulation shown in Figure 5 where the steady-state wage gap values have been calculated for a range of A_H levels.[17] One set of the wage gap values is derived under the condition that h^* does not respond to technical change as in the standard SBTC (depicted by the red-line); for the other set, the stock of skilled workers endogenously grows with technical change (depicted by the blue dashed line). The moderating effect on the wage gap when the aggregate skill-supply responds endogenously to technical change is evident.

1.4.3 Effect on Intergenerational Mobility

From the previous exposition, it has been established that an increase in A_H will lead to a rise in ω^*in the new steady-state equilibrium. As both p_H^* and p_L^* are increasing in ω^*, this implies that the probability of children becoming skilled are enhanced for both skilled and unskilled households when there is an increase in A_H. Thus, technical change is found to improve absolute skill mobility. The effect on relative skill mobility can be observed using the odds-ratio, ρ^*. Technically, relative mobility is said to improve/increase when ρ^* rises, i.e. both p_H^* and p_L^* increase, but p_L^* increases at a faster rate.[18] It is straight-forward to establish that the effect of an increase in ω^* (from $A_H \uparrow$) on ρ^* is positive:

$$\frac{\partial \rho^*}{\partial \omega^*} = \frac{a_L\beta(\gamma-\theta)\{a_H\beta(\gamma-\theta)\omega^*-1\} - a_H\beta(\gamma-\theta)\{a_L\beta(\gamma-\theta)\omega^*-1\}}{\{a_H\beta(\gamma-\theta)\omega^*-1\}^2}$$

$$= \frac{\beta(\gamma-\theta)(a_H-a_L)}{\{a_H\beta(\gamma-\theta)\omega^*-1\}^2} > 0 \tag{1.27}$$

Proposition 3: *Technological change leads to improvements in both absolute and relative intergenerational mobility of skills. However, the odds-ratio continues to be below 1, meaning that children from skilled households continue to have a higher probability of staying skilled, than children from unskilled households transitioning into the skilled state.*

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[17] Figure 5 has been simulated by setting the relative level of skill-biased technology at 2 (i.e. $A_H/A_L = 2$), and then increasing it in increments of 0.5. Model parameters have been set as follows: $a_H = 1$, $a_L = 0.5$, $\gamma = 2$, $\theta = 0.5$, based on previously outlined assumptions. The values of β and v have been taken from the literature, and set as $\beta = 0.98$ and $v = 0.33$ (Autor, Katz, & Krueger, 1998).

[18] The odds-ratio can also rise when both p_H^* and p_L^* decrease, but p_H^* decreases at a faster rate. However, since I am more interested in examining the case of technological improvements, and it is known that this will increase p_H^* and p_L^*, I will ignore the case where the probabilities are reducing.

Figure 6 visually demonstrates how relative skill mobility improves across steady-states, as the values of A_H are increased. The increasing returns to skill motivate an increase in intergenerational transfers by both types of parental agents, improving absolute mobility. As the low-skilled households are at lower probability levels, they experience higher relative improvements when transfers are increased, given the assumption of diminishing returns in human capital investments. This leads to a rise in the odds-ratio across steady-states.

1.5 Conclusion

In the current literature, skill-biased technical change (SBTC) has been predominantly associated with causing a sharp rise in wage inequality. An area which has been left unexamined, however, is how this increase in the returns to being skilled might have potentially impacted the intergenerational mobility of skills. In this paper, I explore the link between skill-biased technology and the intergenerational mobility of skills, using the channel of intergenerational transfers.

To better understand the intergenerational effects of SBTC, I set up an intergenerational framework within the SBTC model, where heterogeneously-skilled households make intergenerational transfers that determine the skill outcome of the next generation. The transfers include a time input and a capital input, and it is assumed that the investments are subject to diminishing marginal returns but are complementary to parental skill-type. SBTC influences these transfers by shaping income levels of parents in the current period and the expected returns to skill in the next period. For a given level of the skill-biased technology factor, I show that the aggregate stock of skilled workers in the model economy reaches a steady-state level which is unique and stable. This also leads to steady-state solutions for the wage levels of the two worker-types, the skill premium, and the intergenerational investment levels. An exercise in comparative statics then reveals that technical change, by increasing the returns to skill, leads to increases in intergenerational investments which improve both absolute and relative intergenerational mobility of skills.

The positive impact of skill-biased technology on intergenerational mobility is intuitively explained by some basic dynamics. First, changes in the returns to skill lead to changes in intergenerational investment decisions. The intensity of intergenerational transfers determine the level of mobility in the model, and forward-looking parental agents (of both types) are motivated to make larger intergenerational investments when the returns to skill increase with technological change; this improves absolute skill mobility in the model. Second, these intergenerational investments are subject to diminishing returns at individual levels. Thus, low-skilled households, who have lower probability levels of becoming skilled, experience larger improvements at the margin when intergenerational transfers are adjusted; this improves relative skill mobility in the model.

By exploring the link between skill-biased technology and intergenerational mobility, this model developed here contributes to two important strands of economic literature. One is the literature on intergenerational mobility, where this research proposes that SBTC can be a possible determinant of skill mobility. Second is the literature on SBTC itself, where the predominant focus so far has been to see how SBTC increases the wage gap between differently skilled people; the work here offers a new perspective, suggesting that SBTC, by positively impacting intergenerational investments, can improve the skill status between different generations of the same family.

The innovation of the model developed in the paper is that it is the first (to the best of my knowledge) to incorporate an intergenerational framework within the standard SBTC model. This not only helps us to observe the impacts of technology on intergenerational investments decisions, but it also creates a version of the SBTC model where the skill-supply is endogenized. Going forward, it is possible to think of further attributes which can be added to this "base" model to make it richer. For example, one such modification can be including a subsistence consumption level in the model. In the current version, the only lower-bound condition on the consumption is that it has to be non-zero. This has implications towards the levels of intergenerational transfers that can be potentially made by agents. If agents do not need to earn a minimum income level for subsistence consumption, this means that they can afford to spend more time at home; they are also less constrained to divert resources from their own consumption towards capital-expenditures for their children. Another factor which could be included in the model is to consider that there are indivisibilities in investments in human capital. Such modifications could enable us to see how earnings, skill-creation and mobility will evolve when additional constraints are imposed on intergenerational transfers. This is left for future research.

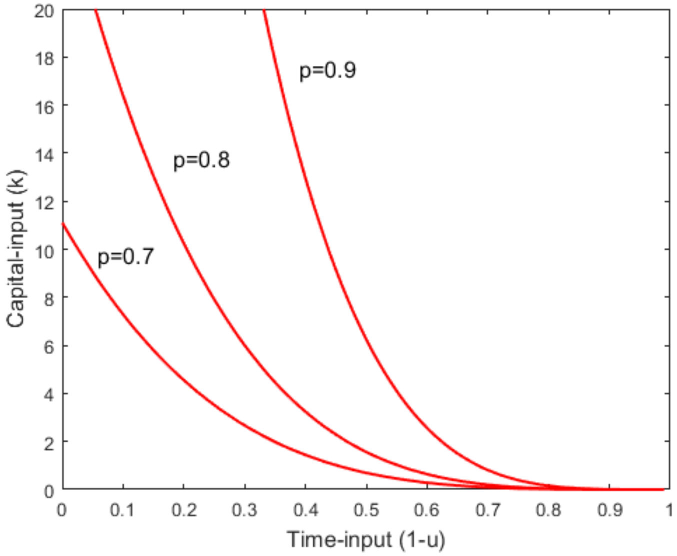

Figure 1: Isoquant Map Based on Probability Function (Equation 1.3)

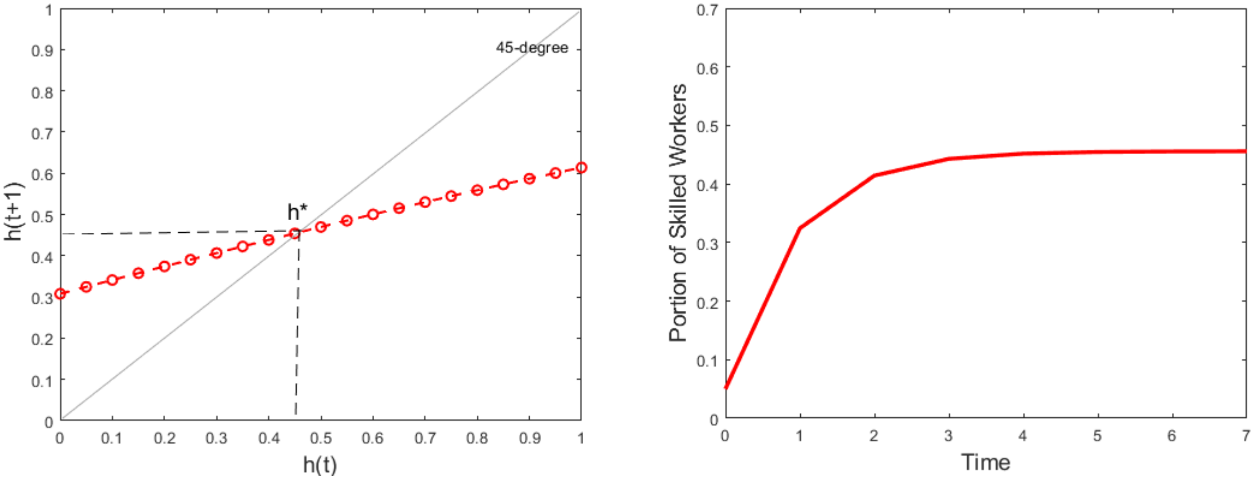

Figure 2: Law of Motion: Portion of Skilled Workers (h)

Figure 3: Time-Path of h to Steady-State

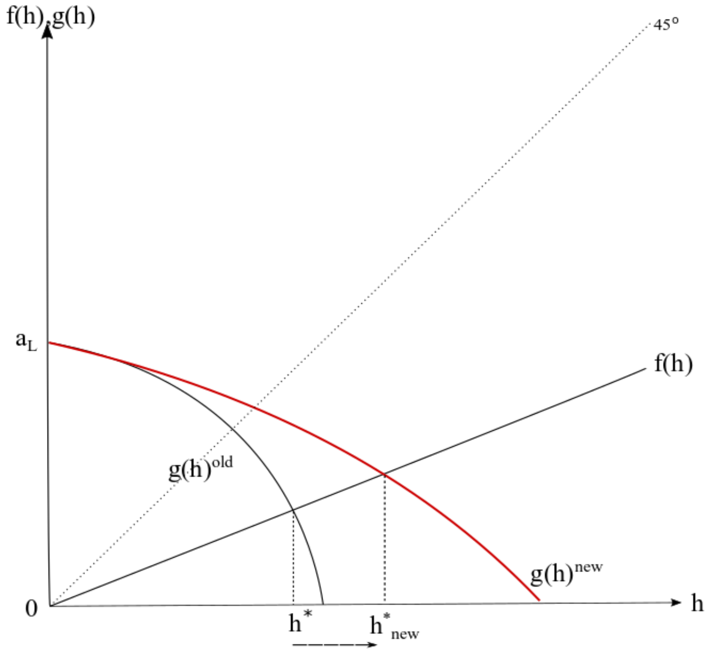

Figure 4: Comparative Statics: Change in h^* from Technical Change ($\uparrow A_H$)

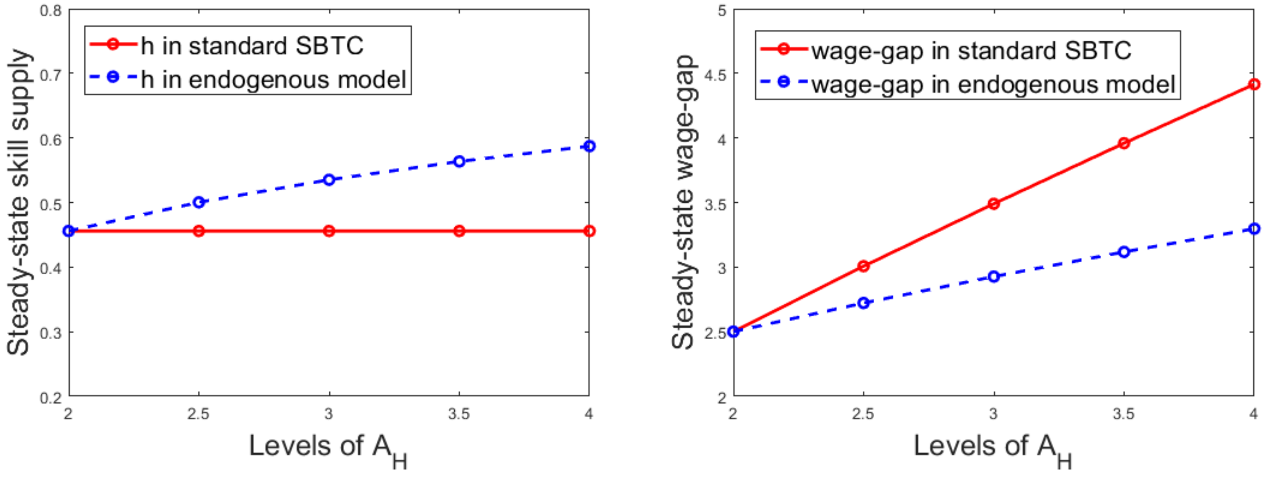

Figure 5: Steady-State Levels of Skill Supply and Wage Gap: Standard SBTC vs. Endogenous Model

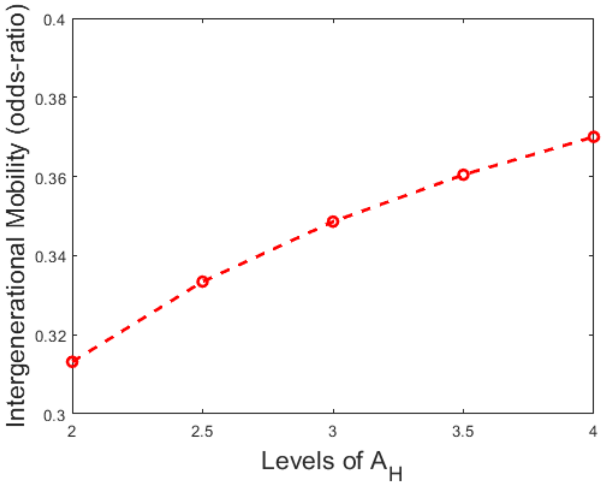

Figure 6: Relative Mobility Levels with Technical Change

2 Does Skill-biased Technical Change Improve Intergenerational Mobility of Skills? Evidence from U.S. Commuting Zones

2.1 Introduction

The primary result of the theoretical model described in Chapter 1 is that when an economy experiences skill-biased technical change, there would be increases in intergenerational mobility in both absolute and relative terms (along with increases in the skill premium and the portion of skilled workers). These results can also be applied to a cross-economy perspective- i.e. if a cross-section of economies is taken at a given period, those characterized by higher technology levels should also have higher levels of intergenerational mobility. A source to conduct this kind of cross-sectional analysis comes from the study of Chetty et al. (2014) on intergenerational mobility in the United States. Using federal income tax records of more than 40 million children and their parents between 1996 and 2012, the study provides intergenerational measures of both income and education outcomes for commuting zones across the country. The highlight of the study is that it finds substantial variation in intergenerational mobility across these areas, leading the authors to describe the U.S. as "a collection of societies, some of which are 'lands of opportunity' with high rates of mobility across generations, and others in which few children escape poverty" (2014, pg. 1).

In Chapter 2, I seek to empirically validate the results of the theoretical model by exploiting this regional variation in intergenerational mobility. I treat the CZs as our economic units, and then proceed to analyze if areas characterized by higher levels of technology have higher mobility in the year 2000. For intergenerational mobility, I look at data from Chetty et al. (2014) on the probability that a child from a specific CZ will attend college, conditional on his/her family being in the 25th percentile (with annual earnings of \$28,800) or the 75th percentile (with annual earnings of \$95,100) of the U.S. national income distribution.[19] Following the standard assumption where college-equivalent workers are considered high-skilled, this metric corresponds to how skill mobility is measured in

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[19] Chetty et al. (2014) compute the national income distribution by averaging family incomes over the five years from 1996 and 2000. All figures are reported in 2012 dollars, after adjusting for inflation using the consumer price index.

the theoretical model described in Chapter 1- i.e. the probability that a child will become skilled, given his/her parent is a low or high skill/income type.[20]

Since technology is not directly observable, the usual approach to calculate technology levels is through the use of proxies, as commonly found in several wage-studies. I focus on using the share of high-technology occupations per CZ, calculated as the number of STEM (Science, Technology, Engineering, and Mathematics) workers out of total employed, as the proxy measure for technology as this can be constructed from Census micro-data. However, a concern with using a STEM-based technology measure is that there is the potential for endogeniety, given the study's particular approach to measuring intergenerational mobility using the rate of college incidence. To address this issue, I construct a Bartik-type instrument (Bartik, 1991; Blanchard & Katz, 1992; Autor et al., 2013) for the technology measure, where industry-level STEM shares in a CZ are estimated using lagged values (from 1970) and growth rates at the national-industry level.

From 2SLS estimations, I find that the probability of attending college for children from low-income households (ranked in the 25th percentile nationally) improves by 1.3 percentage points if they live in a CZ which is 1 standard deviation (SD) above the mean technology score. Moreover, the increase in college attendance rates for high-income households (ranked in the 75th percentile nationally) is smaller at 0.55 percentage points, implying that there is a relative improvement for lower income households. This would mean that a child from a low-income household would be 5 percentage points more likely to attend college if he or she lived in a CZ ranked in the top decile of the technology distribution, compared to living in a CZ from the bottom decile; for a child from a high-income household, this increase would be 2.2 percentage points. Hence, the empirical work here suggests that SBTC has played a role in enhancing both absolute and relative intergenerational mobility of skills, validating the results of the theoretical model developed in the earlier chapter.

Two other propositions from the theoretical model is that technological change will increase both the supply of skills and the skill-premium. This is an important property of the model, as the subsequent improvement in intergenerational mobility is linked to this

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[20] Note that in the SBTC model, a higher skill level is synonymous with a higher income level. This correlation is also found empirically. Using 2000 Census data, I calculate the relationship between college completion rates and a household's position in the income distribution. I find that for households who are in the top quartile of the income distribution, around 45% of members aged 24 years or higher have reported completing a college degree or more; for households in the bottom quartile, this portion is only 15%.

increase in the skill-premium (which incentivizes parents to make larger intergenerational transfers). To test these two propositions, I construct relevant labour market measures at the CZ level from U.S. Census data. The skill-premium (returns to skill) for a CZ in a given year is estimated by running a wage regression. The log of hourly wages of full-time, full-year workers (aged 18-64 years) are regressed on an education dummy, which is set to 1 for respondents who have attended at least 1 year of college (i.e. some college or more). The supply of skilled workers for a CZ is computed based on the portion of workers who have completed at least one year of college education. The empirical investigation also finds strong, positive correlations between technology, the skill premium and the supply of skills- a CZ which lies 1 SD above the mean technology level (in the year 2000) is found to have a skill-premium level which is 2.2% higher, as well as the fraction of skilled workers in their workforce being 4 percentage points larger. The impact of technological change is also assessed using a stacked first-difference approach between 1980-2000, revealing that CZs with higher levels of technological growth had a congruent increase in their skill-premium levels and the supply of skilled workers within this period.

The findings of the chapter contribute to both intergenerational mobility and SBTC literature. In context of the former, the research here complements the work from Chetty et al. (2014), where the correlations between intergenerational mobility and a set of observable CZ characteristics are highlighted.[21] However, any potential relationship between technology and mobility is left unexamined in their work, whereas the research here finds a causal link using a method of IV estimation, and thus proposes that SBTC has a positive impact on intergenerational mobility. In context of the later, while skill-biased technology has been conventionally associated with increasing wage inequality among the same generation, the empirical work here finds that SBTC can also improve skill status between different generations of the same family. This can potentially lead to changes in income levels from an intergenerational perspective, a phenomenon that has not been explored in previous SBTC literature.

In the next section, more details are provided on how the empirical indicators have been calculated for the study, along with the data sources. This is followed by a description of the key regression of interest, which is used to identify the link between technology and mobility. Section 2.4 then describes the endogeniety concerns of the study, followed by how the Bartik-IV has been constructed to address this problem. Following this, the

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[21] The research from Chetty et al. (2014) looks at correlations between intergenerational mobility (income and education) and a set of 28 different CZ level characteristics, which cover categories like race, income, schooling, social factors, family characteristics, tax rates, etc.

main findings from the regression analysis (OLS and 2SLS) are presented and analyzed. Section 2.7 concludes the chapter, and mentions possible areas for extending the research.

2.2 Data and Indicators

2.2.1 Geographical Units

The primary study units for the empirical analysis are commuting zones. Tolbert and Sizer (1996) constructed CZs by aggregating counties based on commuting patterns from the 1990 Census, and their use in economic literature was first introduced by Dorn (2009). CZs cover the entirety of the U.S., including rural areas, and the total number of CZs in 2000 was 741.

Commuting zones are particularly relevant as study units for this research, since technology and intergenerational mobility in the model are linked through labour-market earnings. As commuting zones are defined by labour market areas (and not political boundaries, as in the case of counties), they more closely capture the interrelationships between labour demand and supply. Thus, it seems pertinent to study the impact of changes in technology on labour earnings (and subsequently, intergenerational mobility) using data which span both place-of-work and the place-of-residence, rather than just the latter.

In terms of the variables analyzed in the study, the intergenerational mobility measures are provided by Chetty et al. (2014) at the CZ-level. The other key variables of the model- technology levels, skill-premium and supply of skills- are measured using IPUMS Census data (Ruggles, Flood, Goeken, Grover, Meyer, Pacas & Sobek, 2019) from 1970, 1980, 1990 and 2000. In order to calculate these estimates at the CZ-level, I make use of the local labour market cross-walk files provided by Autor and Dorn (2013), which provide a probabilistic matching of the smallest Census geographic units (counties for 1970, 1980; Public Use Microdata Area for 1990, 2000) to the commuting zones.

2.2.2 Explanatory Variable: Technology Measure

Since technology is not directly observable, the usual approach to calculate technology levels is through the use of proxies, as commonly found in several wage-studies. For example, in their study on how technology can impact wages and the education premium, Bartel and Sicherman (1999) showcase a comprehensive list of six technology measures.[22] A limitation of most of these measures (specifically, the measures 1 to 5 as described in the footnote) is that the data is only available at the national industry level, which makes them unsuitable for a commuting zone-level analysis. Consequently, I focus on using the share of high-technology occupations per CZ, calculated as the number of STEM workers out of total employed, as the proxy measure for technology (as this can be constructed from Census micro-data).[23]

There are two perspectives which support why the portion of STEM workers employed can be a good indicator of the technology level. One, if technology is changing at a faster rate, workers are required to make more frequent changes in the tasks they do (Jovanovic & Nyarko, 1995). Thus, high-technology areas would have a higher concentration of skilled and educated workers who are able to adapt to these changes, such as those with a STEM background.[24] A second perspective is that industries which employ more advanced and high-tech capital would have a higher demand for more skilled workers, under the assumption that physical and human capital are gross complements. This would consequently imply that areas with more high-tech capital should have more STEM workers.

To construct a technology measure at a CZ level (c), I make use of a list of STEM occupations provided by the U.S. Bureau of Labour Statistics.[25] The index is constructed for time t by calculating the number of workers in these STEM occupations over total

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[22] These six measures are "(1) total factor productivity (TFP) growth calculated by Jorgenson, Gollop, and Fraumeni (1987); (2) the NBER TFP growth series described in Bartelsman and Gray (1996); (3) the ratio of investment in computers to total investments as reported in the 1987 Census of Manufactures; (4) the ratio of R & D funds to net sales reported by the National Science Foundation (1993); (5) the number of patents used in the industry, calculated by Kortum and Putnam (1995); and (6) the ratio of scientific and engineering employment to total employment calculated from the 1979 and 1989 CPS by Allen (1996)" (1999, pg. 290).

[23] An alternate measure of high-technology, based on region-level data, comes from Devol, Wong, Catapano and Robitshek (1999). They look at the percentage of a region's total economic output that comes from high-technology industries, in relation to national output levels. These measures were, however, initially only calculated for metropolitan areas in the U.S, due to the lack of GDP data at the county-level. County-level GDP statistics were made available from the U.S. Bureau of Economic Analysis only after 2012.

[24] In a new paper, Deming & Noray (2020) verify how STEM workers are engaged in jobs that are at the forefront of technological change. Using job vacancy data between 2007 and 2009, they find that job ads which went through the highest rate of change in skill requirements over this period are STEM occupations.

[25] The list of STEM occupations from the Bureau of Labour Statistics is available at www.bls.gov/oes/stem_list.xlsx.

employment ($N_{c,t}$):

$$Tech\ Measure_{c,t} = \frac{STEM_{c,t}}{N_{c,t}} \tag{2.1}$$

The process of using Census data to calculate Equation (2.1) is described in detail in Appendix B1.

2.2.3 Outcome Variables

Intergenerational Mobility Measures

To measure mobility, I use the education mobility measures from Chetty et al. (2014), which show the probability a child will attend college, conditional on the rank of his/her family in the U.S. national income distribution. The primary respondents of the study are U.S. citizens in the 1980-1982 birth cohorts, who are categorized as the *children* group. The income of the parents of these children are measured as mean family income between 1996 and 2000, when the children were between 15 and 20 years old. To derive the education mobility measures, Chetty et al. (2014) look at the portion of the children group who attended college when they were between 18-21 years old; the presence of the 1098-T form (filed by a college on behalf of the student) is used to identify if the child is attending college. This data (along with parental incomes) is then used to construct the education mobility measure for each commuting zone for the year 2000, with children being assigned to commuting zones based on the location of their parents when the child was claimed as a dependent (irrespective of where they live as adults).[26] The rates are reported for a total of 709 CZs (out of 741), with at least 250 children in their core sample.

Given that the relationship between college attendance rates and parental income rank at the national level is found to be very linear (with a slope of 0.675), Chetty et al.

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[26] The method used by Chetty et al. thus disregards any incidence of geographical mobility, as a child's location of college attendance does not have to be the same as the location where he/she was claimed as a dependent (for example, 83.5% of the children in their sample were found to be living in the same CZ where they were claimed as dependents by the time they were 16 years old; 62% lived in the same CZ by the time they were 30 years old). However, the fundamental assumption made in the model is that parents are investing in the skill-development of their children- in this context, it is the location of the parents that is important as it determines their income source and levels, and subsequently their ability to invest in their children. Thus, it is suitable to use the parent's location to construct college attendance rates for CZs.

(2014) summarize the data by using a linear regression function. This function is found by regressing the college attendance indicator of the child on the parent's national income rank. Denoting C_{jc} as the college indicator of a child j from CZ c, and I_{jc} to be the parent's rank in the income distribution of parents in the core sample, the linear function for CZ c is presented as:[27]

$$C_{jc} = \alpha_c + \beta_c I_{j,c} + \varepsilon_{j,c} \tag{2.2}$$

The regression results are then used to calculate, for each CZ, the expected college attendance rate of children born to parents from a specific income rank ($\bar{c}_{pc}$):

$$\bar{c}_{pc} = \alpha_c + \beta_c i \tag{2.3}$$

where i is the income rank of parents in the national distribution. Chetty et al. (2014) report $\bar{c}_{pc}$ specifically for children who have parents at the 25th percentile, i.e. when $i = 25$. Using the β_c and the $\bar{c}_{25c}$ values provided, it is straightforward to calculate the intercept α_c for each commuting zone. Equation (2.3) can then be used to calculate the expected education mobility measure for a CZ for any income percentile, by setting the appropriate value of i. For the analysis here, I make use of $\bar{c}_{25c}$ and $\bar{c}_{75c}$, i.e. the college attendance rate for children from CZ c, given that their parents are at the 25th percentile or the 75th percentile of the national income distribution. These are the measures of absolute mobility, corresponding respectively to p_L and p_H from the theoretical model in Chapter 1. Relative mobility is then calculated by taking a ratio of $\bar{c}_{25c}$ and $\bar{c}_{75c}$ (to match how I have calculated the odds-ratio, ρ).

Labour Market Outcomes

The skill-premium (returns to skill) for a CZ in a given year is estimated by running a wage regression. The log of hourly wages of full-time, full-year workers (aged 18-64 years) are regressed on an education dummy, which is set to 1 for respondents who have attended at least 1 year of college (i.e. some college or more). A vector of control variables that include gender, two race/ethnicity categories (Black, Hispanic), place of

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[27] In their paper, the linear regression function is presented (in pg. 24) using income mobility measures. I have presented a reformatted version in (2.2) using education measures, as Chetty et al. describe both equations to be structurally similar.

birth (U.S. vs. foreign born) and a quartic in age are included in the regression to control for demographic differences among the workers. The coefficient of the education variable from this regression analysis is then used to measure the skill-premium for each CZ- i.e. the wage gap accounted for by differences in the education background of workers in that location.

The supply of skilled workers for a CZ is computed based on the portion of workers who have completed at least one year of college education. Appendix B2 provides more details on how the labour market outcomes have been measured.

2.3 Key Regression of Interest

To test the key prediction of the model- that technical change has a positive link with intergenerational mobility- the following cross-sectional regression is constructed:

$$IG\ mobility_c = \phi + \beta(Tech\ Measure_c) + \theta X_c + \delta_{s(c)} + \mu_c \tag{2.4}$$

The main outcome variable, $IG\ mobility_c$, is the CZ-specific education mobility measure; the main explanatory variable, $Tech\ Measure_c$, is the CZ's share of STEM workers. The key hypothesis of the study is that $\beta > 0$. To more effectively isolate this impact of the technology factor, I include a set of three CZ-level demographic descriptors (X_c) in the regression which could be potential confounders. The first factor is a CZ's share of African-American population, which is highlighted by Chetty et al. (2014) as being one of the spatial factors that is more strongly correlated with mobility. Areas with large African-American populations in the U.S. are recognized to have developed with institutions and industries which are different from other locations. By controlling for the racial composition of the CZ, I hope to eliminate the impact of these channels on the development of intergenerational mobility. The second factor is the fraction of foreign born population in a CZ, as it is likely that a portion of them had their education outcomes influenced by foreign labour earnings. The third is the (log) population size of the CZ, as the size of an area can have an impact on its overall development, which in turn could impact mobility. State-level fixed effects are also included in the regression as technology levels, institutions, etc. are observed to vary significantly by states in the U.S.[28] Hence,

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[28] One such measure of technology at the state level is the State Technology and Science Index (STSI)

identification is obtained solely from variation across CZs within a state (after controlling for variables in X_c).

2.4 Endogeneity Issues and IV Strategy

Given this study's particular approach to measuring intergenerational mobility (the rate of college incidence) and technology levels (the share of STEM workers), there can be potential endogeneity issues. Areas with higher intergenerational mobility (in absolute terms) would be characterized by a higher portion of college-educated workers in the population. This can potentially impact both the numerator and denominator of the technology measure given in (2.1)- i.e. there can be more workers who are of the STEM profile, as well as a higher employment level in that area overall. This creates an issue with causal identification, as intergenerational mobility levels can be potentially affecting the technology measure constructed for the CZ.

In order to address this simultaneity bias, I construct a Bartik-type IV (Bartik, 1991) for the technology measure.[29] I first consider a baseline measure of technology level for each CZ from a lagged point in time- the year 1970- by looking at industry-level STEM shares within that CZ. National-level industry data are then used to calculate growth rates in the share of STEM workers per industry at the national level in the U.S. between 1970 and the year of interest (t). The national-level industry growth rates are then universally applied across all CZs, to estimate how their baseline industry-level STEM shares would have grown from 1970 to the year t if the growth was only driven by national level shocks. A technology instrument is then constructed using these extrapolated numbers, which is considered to be exogenous under the assumption that national-level changes in the STEM intensity of different industries are not impacted by intergenerational mobility at the CZ level, or other omitted variables in μ_c in Equation (2.4).[30]

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from the Milken Institute (Kloweden, Lee & Ratnatunga, 2018). This index measures states on their science and technology capabilities, giving each location a composite score based on five broad factors: research and development (R&D) inputs, risk capital and entrepreneurial infrastructure, human capital investment, technology and science workforce, and technology concentration and dynamism. The ranking shows significant variation at the state-level- for example, in 2018, the top-technology state was Massachusetts with a score of 86, while the bottom ranked state, Mississippi had a score of 19.

[29] This type of IV is also commonly referred to in the literature as the "shift-share" instrument.

[30] The research is thus using a quasi-experimental design where differences in technology levels across CZs are inferred based on initial industry shares in 1970. A potential issue with this identification strategy can arise if the initial industry shares themselves are not exogenous- for example, if there were (unobserved) CZ-level characteristics in the past which made certain locations more predisposed to having

Specifically, if one wants to calculate Equation (2.1) for year t using lagged values from 1970, the approach would be as follows:

$$Tech\ Measure_c = \frac{\sum STEM_{i,c,1970}(1 + gSTEM_{i,c,1970-t})}{\sum N_{i,c,1970}(1 + gN_{i,c,1970-t})} \tag{2.5}$$

where $gSTEM_{i,c,1970-t}$ denotes the growth in the number of STEM workers and $gN_{i,c,1970-t}$ denotes the growth in total employment for industry i in CZ c between 1970 and the year of interest. To construct the IV, I focus only on national-level industry growth rates, and estimate the technology IV as:

$$Tech\ Measure_c^{IV} = \frac{\sum STEM_{i,c,1970}(1 + gSTEM_{i,1970-t})}{\sum N_{i,c,1970}(1 + gN_{i,1970-t})} \tag{2.6}$$

where $gSTEM_{i,1970-t}$ denotes the growth in the number of STEM workers and $gN_{i,1970-t}$ denotes the growth in total employment for industry i at the national level (the process of using Census data to calculate the IV is described in Appendix B1).

2.5 Summary Statistics

Table 1 displays the summary statistics of the key variables for the empirical analysis. The statistics are reported at the CZ level in the year 2000, and have been calculated using the CZ's share of national population as weights.

The average portion of STEM workers out of total employed in a CZ, which serves as the measure for technology, is found to be 6.3%, with a SD of 2.3%. The fairly high value of the SD (over one-third of the mean) indicates that, as one would expect, CZs in the U.S. are widely dispersed when it comes to technology levels; this can also be seen in the distribution plot (Figure 7) which is right-skewed (with a skewness value of 0.828). For example, the average STEM share for a CZ ranked in the top decile of the technology distribution in 2000 is found to be 10.9%; for a CZ from the bottom decile, this average is 2.9%.

STEM-intensive industries, as well as motivated parents to make higher investments in education over time. In this case, the 2SLS estimator calculated using the Bartik instrument might be inconsistent (see Pinkham, Sorkin & Swift, 2018).

A list of the 10 CZs with the largest STEM shares is provided in Table 2. Most of the locations on the list are reputed to be technological hubs- for example, the CZ with the highest STEM share is San Jose in California, which is recognized as a notable center of innovation and technology (the location of Silicon Valley). Other locations in the top 5 include Washington DC (the administrative center), Raleigh in North Carolina (the Research Triangle region), Huntsville in Alabama (location of NASA's space flight center) and Austin in Texas (a hub for Fortune 500 companies).

In terms of absolute intergenerational mobility, the mean college attendance rate among children from the low-income households (25th percentile) is 42.6% (S.D. of 7.04), while for children from the high-income households (75th percentile), this rate is 76.1% (SD of 4.2). The mean of this odds-ratio (which captures relative mobility) is 0.56.

From the wage regression analysis, the mean education-premium is found to be 0.33 log-points; this implies that within a CZ, log hourly wages for workers with some college education in the sample are 39% higher [exp(0.33)-1] compared to workers who have not attended college (conditional on other observables).

2.6 Results

2.6.1 Intergenerational Mobility and Technology

Three types of dependent variables are analyzed separately using regression Equation (2.4)- absolute intergenerational mobility for the low-income and high-income groups, and relative intergenerational mobility (the odds-ratio). The intergenerational mobility measures are observed at the CZ-level (a total of 709 locations) for the year 2000, and each observation is weighted by the CZ's population.

Absolute Intergenerational Mobility: Low-Income Group

Table 3 reports the regression results from OLS estimations, where the dependent variable used is the college attendance rate of children from low-income households (25th percentile), and the explanatory variable is the technology measure from Equation (2.1). The first column estimates Equation (2.4) using only the technology measure, which yields a coefficient of +0.7 (P-value<0.001). The interpretation of this coefficient is that a 1%

increase in the technology measure would increase the college attendance rate of children from low-income households by 0.7 percentage points. In the second column, the specification controls for the three demographic factors (fraction black, fraction foreign born and log population size) and it is observed that the technology coefficient reduces to +0.37, but remains positive and significant. In column (3), state-level fixed effects are then added to the regression. This is the preferred specification of the study, as it only exploits variation across CZs within states. I find that the magnitude and significance of the technology coefficient remains intact in this specification.

As the availability and cost of education can be influential in determining education outcomes, I add two supply-side controls in regression model (4)- these include the number of colleges per capita and the average level of college-tuition fees in a CZ.[31] The sample size is reduced to 580 for this specification, as CZs which do not have any degree-offering institutions are dropped from the analysis. The coefficient for the technology measure is not impacted by the addition of these supply-side factors.

Finally, in column (5), I focus specifically on a subset of urban CZs, which are defined as locations that overlap with Metropolitan Statistical Areas (MSAs). Such areas, which have a high population density at the core, are characterized by accentuated levels of industrialization, commerce, amenities, social networks etc. which can potentially impact intergenerational mobility. The relationship with the technology measure remains positive and significant, and the β coefficient is measured to be +0.41 among this sub-sample of 321 urban CZs.

Given the potential endogeneity issues highlighted earlier, I next run a series of 2SLS estimations, where the Bartik-type IV is used. In the first-stage, I regress the technology measure on the technology IV (from Equation 2.6), keeping the relevant control variables for each model. The first-stage estimates are reported in Table 4. Across all specifications, the IV is found to be positively correlated with the technology measure, with P-values less than 0.001. The F-statistics for all first-stage specifications are also larger than 10, supporting the case that the technology IV constructed is a strong instrument.

The 2SLS results are reported in Table 5. The 2SLS coefficients for the technology measure are positive and significant across all of the 5 specifications described earlier, and they are

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[31] Data on the supply side factors are taken from Chetty et al. (2014). They calculate the number of colleges per capita in each CZ as the number of institutions in the 2000 IPEDS divided by the CZ population. The college tuition is calculated as the mean tuition and fees for first-time, full-time undergraduate students for the institutions in each CZ.

all found to be larger than the corresponding OLS coefficients. As specified earlier, OLS is subject to endogeniety concerns due to both simultaneity bias and the possibility of omitted variables. In the case of omitted variables, for example, such unobservables could be local labour market shocks (like levels of unionization, globalization, privatization etc.) that are positively correlated with technological development, but negatively correlated with intergenerational mobility due to adverse impacts on wages. This can explain the negative bias in the OLS estimates.

From 2SLS estimation, the value of β is +0.58 in the preferred model with the state-level fixed effects (column 3). This indicates that college-attendance rates for children from low-income households would improve by 1.3 percentage points if they are in a CZ which lies 1 SD above the mean technology level.

Absolute Intergenerational Mobility: High-Income Group

In Table 6, results are reported from the regression analysis where the dependent variable used is the college attendance rate of children from high-income households (75th percentile). Panel A reports the results from the 2SLS estimation, while Panel B provides the OLS coefficients for the technology measure for comparison, for the same set of specifications. Using the technology coefficient from the preferred 2SLS model (panel A, column 3), college attendance rates for high-income households are predicted to be 0.55 percentage points higher in CZs that lie 1 SD above the mean technology level. The coefficients, however, are noticeably smaller than in Table 5, suggesting that relative improvements are larger for lower income households, something I confirm in the analysis that follows.

Relative Intergenerational Mobility

In order to measure the impact of technology on intergenerational mobility across different income groups, I examine the odds-ratio (measured as p_L/p_H in the theoretical model). The odds-ratio is calculated as the ratio of the college attendance rate between low-income and high-income households; an improvement in this odds-ratio signifies that the children from the lower-income group have improved their probability of attending college, relative to the children from the higher-income group.

The results of the regression model in Equation (2.4) using the odds-ratio as the dependent variable are reported in Table 7. The coefficients for the technology measure are found to be positive and significant in all of the specified regression models (both 2SLS and OLS); for the preferred 2SLS specification (panel A, column 3), the coefficient is +0.60.

This impact of technology on the odds-ratio, taken in conjunction with the findings on absolute mobility, supports the theoretical results found earlier in Chapter 1: technological change will not only improve the absolute education outcomes of households across generations, but it will also lead to larger improvements for the low-income group relative to the high-income group. Specifically, the regression results indicate that a child at the 25th percentile of the national income distribution would be 5 percentage points more likely to attend college if he or she lived in a CZ ranked in the top decile of the technology distribution, compared to living in a CZ from the bottom decile; for a child at the 75th percentile, this increase would be 2.2 percentage points.

2.6.2 Labour Market Outcomes and Technology

In the theoretical SBTC model with the intergenerational framework developed in Chapter 1, technological change increases both the supply of skills and the skill-premium. This is an important property of the model, as the subsequent improvement in intergenerational mobility is linked to this increase in the skill-premium (which incentivizes parents to make larger intergenerational transfers). In the final part of the empirical analysis, I examine the impact of technology on the fraction of skilled workers and the skill-premium at the CZ level. The regression analysis is done in two parts. The first is a cross-sectional analysis of CZs in the year 2000 to examine how levels of the skill supply and the skill-premium are related to technology levels, while the second examines how changes in technology between the period 1980-2000 impacted the growth of these variables.

Analysis of Levels in 2000

Table 8 reports the regression results that show the impact of technology on labour market outcomes in the year 2000. The results given in columns (1) to (3) have the fraction of skilled workers for each CZ as the dependent variable. Models are initially analyzed using only the technology measure as the explanatory variable, before controls are added (fraction black, fraction foreign born, population size, and state-level fixed effects) at subsequent stages. The coefficient of the technology measure is found to be positive and significant across all specifications, indicating that areas with exogenously higher technology levels (as predicted by the IV) are observed to have a higher portion of skilled workers in their workforce. From the preferred 2SLS regression model, where all controls are used (panel A, column 3), the coefficient of the technology measure is found to be +1.73, implying that in a CZ which lies 1 SD above the technology mean, the fraction of skilled workers in its workforce would be around 4 percentage points higher.

The results given in columns (4) to (6) have the estimated skill premium for each CZ as the dependent variable. Again, all the estimated coefficients of the technology measure are found to be positive and significant. From the preferred 2SLS model (panel A, column 6), the estimated coefficient for the technology measure is +0.01 log points; thus, a CZ which lies 1 SD above the mean technology level would have a skill-premium level which is 2.2% higher. In other words, hourly wages for workers with some college education are approximately 8% higher if they work in a CZ which is at the top decile of the technology distribution, compared to working in a CZ from the bottom decile.

Analysis of Changes between 1980-2000

The second part of the analysis examines how changes in technology levels are correlated to changes in the skill-premium and changes in the fraction of skilled workers at the CZ-level. The period I focus on is 1980 to 2000. When estimating these regression models, I follow a stacked first-differences approach (Autor et. al, 2013). The values of all the primary variables are calculated initially for three points in time- 1980, 1990 and 2000- at the CZ level. I then calculate the ten-year first-differences for the two periods- 1980 to 1990 and 1990 to 2000- and stack the values, incorporating a time dummy for the second decade. The other control variables in the model (fraction black, fraction foreign born and population size) are all measured at the start of the decade.

Columns (1) to (3) of Table 9 report the results from regressing the changes in fraction of skilled workers on changes in the technology measure. From 2SLS estimations (panel A), the coefficients of the main explanatory variable are found to be positive across all specifications; however, the result is only significant for column (2).

The results from regressing the changes in skill premium on changes in the technology measure are then presented in columns (4) to (6). Here, the coefficients of the technology measure are found to be positive and significant across all the models. From the preferred 2SLS specification (panel A, column 6), the value of the coefficient is +0.02 log points, indicating that CZs which experienced higher technological change over time also experienced a larger growth in their skill-premium levels (with a 1% change in technology level predicted to increase the skill-premium by 2.2%).

Taken in conjunction, the results from the labour market analysis thus verify how technological change can positively impact both the skill-premium and the supply of skills. While the link between technology and skill-premium is a standard result in the canonical SBTC model, the endogenous response of the skill-supply to technological change is an unique property of the SBTC model with the intergenerational framework developed here. This property is crucially validated by the empirical evidence.

2.7 Conclusion

In the current literature, skill-biased technical change (SBTC) has been predominantly associated with causing a sharp rise in wage inequality. An area which has been left unexamined, however, is how this increase in the returns to being skilled might have potentially impacted the intergenerational mobility of skills. In this Chapter, I search for empirical evidence which can validate the key result of the theoretical model developed in Chapter 1- i.e. technical change can improve both absolute and relative intergenerational mobility of skills.

The approach to investigate this prediction is by using education mobility measures from Chetty et al. (2014) and a technology measure computed at the U.S. commuting zone level using the share of STEM (Science, Technology, Engineering, and Mathematics) workers out of total employed. I instrument this measure using a Bartik-type IV to deal with endogeneity concerns. Using 2SLS estimations, I find that the probability of attending college for children from low-income households (ranked in the 25th percentile nationally) improves by 1.3 percentage points if they live in a CZ which is 1 SD above the mean technology level. Relative improvements across income groups are also observed, as I find that the increase in college attendance rates for a high-income household (ranked in the 75th percentile nationally) is lower at 0.55 percentage points. This would mean that a child from a low-income household would be 5 percentage points more likely to attend college if he or she lived in a CZ ranked in the top decile of the technology distribution, compared to living in a CZ from the bottom decile; for a child from a high-income household, this increase would be 2.2 percentage points. Hence, while skill-biased technology has been conventionally associated with wage inequality, the empirical work here suggests that it has also played a role in enhancing both absolute and relative intergenerational mobility of skills.

The empirical investigation also finds strong, positive correlations between technology, the skill premium and the supply of skills at these locations. A CZ which lies 1 SD above the mean technology level (in the year 2000) is found to have a skill-premium level which is 2.2% higher, as well as the fraction of skilled workers in their workforce being 4 percentage points larger. The impact of technological change is also assessed using a stacked first-difference approach between 1980-2000, revealing that CZs with higher levels of technological growth had a congruent increase in their skill-premium levels and the supply of skilled workers within this period.

The findings of this Chapter builds on the important work of Chetty et al. (2014), as they suggest that technology can be a potential causal mechanism behind the substantial variation in intergenerational mobility observed across U.S. commuting zones. The paper also contributes to the SBTC literature, where the predominant focus so far has been to see how SBTC increases the wage gap between differently skilled people; the work here offers a new perspective, suggesting that SBTC can improve the skill status between different generations of the same family, by increasing college attendance rates. As a college education is typically considered to be the main gateway to higher incomes (e.g. Corak, 2013), this would correspondingly lead to improvements in income and social status across generations.

The positive link between SBTC and skill mobility uncovered here opens up an interesting avenue for future research. It is known both theoretically (e.g. Becker and Tomes, 1979; Solon, 1999) and empirically (e.g. Corak, 2013; Chetty et al., 2014) that income inequality can worsen intergenerational earnings mobility. Thus, there appears to be a need for some reconciliation of the two seemingly contradictory results concerning income inequality conditions improving skill mobility on the one hand, but reducing earnings mobility on the other. A possible channel to explain this could be *skill quality*- specifically, how investments in education quality can differ among children from rich and poor households. For example, in their study on the role of colleges in influencing mobility, Chetty, Friedman, Saez, Turner and Yagan (2017) find that a disproportionately large number of students in top-tier colleges in the U.S. come from richer families. Their study uncovers that in Ivy League/elite schools, more than 65% of students come from families who are ranked in the top quintile of the U.S. national income distribution, while the portion of students who belong to households from the bottom quintile is only around 3%. The quality of school then has a significant influence on labour market earnings, with students from elite colleges earning around 2.3 times more than students from lower-ranked colleges once they graduate. In this scenario, skilled children from rich households would end up earning more than skilled children from poor households, explaining why improvements in skill mobility (due to SBTC) may not translate to improvements in income mobility. A formal examination of this hypothesis could give us a more unified understanding of the interlinks between income inequality due to technical change, income mobility and skill mobility. This is left for future research.

Table 1: Summary Statistics: Key Variables for CZs, 2000

	Mean	Standard Deviation	Min	Max
	(1)	(2)	(3)	(4)
Tech Measure: STEM Share of Emp. (%)	6.279	2.266	1.288	15.17
College Attendance | Low Income Rank (%)	42.78	7.048	9.224	71.88
College Attendance | High-Income Rank (%)	76.07	4.200	36.67	98.08
College Attendance Odds Ratio (25/75)	0.559	0.069	0.245	0.821
Portion of Skilled Workers (%)	61.51	7.699	34.25	75.42
Education Premium (log points)	0.335	0.064	0.130	0.477

Notes: Table 1 lists summary statistics for key variables at CZ level (weighted by CZ share of national population), with $N = 741$. Columns (1) and (2) report the mean and SD for the year 2000; Columns (3) and (4) report the minimum and maximum values. The *Technology Measure* is calculated as percentage share of STEM workers out of total employed for the CZ. The *College Attendance Rate for Low-Income Rank* is college attendance by children of parents ranked in the 25th percentile of the national income distribution, while *College Attendance Rate for High-Income Rank* is for parents ranked in the 75th percentile, as measured by Chetty et al. (2014). The odds ratio of college attendance rate is then calculated from these two numbers. *Portion of Skilled Workers* is the fraction of full-time, full-year workers in the CZ who have completed at least one year of college. The *Education Premium* reports the coefficients of an education dummy from a wage regression estimated for individual CZs, where log hourly wage (full-time, full-year workers) have been regressed on an education dummy (some college or more), sex, two race categories (non-white, Hispanic), place of birth, and a quartic in age. Table 2 below lists the Top 10 Commuting Zones ranked by size of the Technology Measure, and reports the average values of the key variables in each location.

Table 2: Top 10 Commuting Zones by Technology Measure, 2000

CZ Name	Population (1)	Tech Measure: STEM share of Emp. (%) (2)	College Attendance Rate (25th Perc.) (%) (3)	College Attendance Odds Ratio (25/75) (4)	Percentage Skilled (%) (5)	Education Premium (log points) (6)
San Jose, CA	2,393,183	15.2	57.2	0.70	73.0	0.47
Washington DC, DC	4,632,415	12.5	45.3	0.59	74.1	0.43
Raleigh, NC	1,412,127	11.5	42.9	0.54	68.9	0.40
Huntsville, AL	519,583	11.5	37.8	0.50	61.9	0.40
Austin, TX	1,298,076	10.7	37.1	0.50	69.5	0.40
Palm Bay, FL	589,177	10.3	48.8	0.60	64.2	0.37
Denver, CO	2,449,044	10.2	40.6	0.56	71.8	0.32
Colorado Springs, CO	4,587,132	9.96	39.4	0.55	71.0	0.29
San Francisco, CA	4,642,561	9.90	60.0	0.73	75.4	0.42
Fredericksburg, VA	241,044	9.82	32.6	0.46	57.5	0.35
All CZ Mean		6.27	42.8	0.55	61.5	0.33

Table 3: Absolute Intergenerational Mobility (Low-Income Rank) and Technology Measure in CZs, 2000: *OLS estimates*

	Dep Variable: College Attendance Rate | Parental Income Rank at 25th Percentile				
	(1)	(2)	(3)	(4)	(5)
Tech Measure	0.700*** (0.113)	0.370*** (0.103)	0.350*** (0.092)	0.358*** (0.100)	0.407*** (0.124)
Percent Black		-0.158*** (0.020)	0.045* (0.264)	0.035 (0.028)	0.036 (0.040)
Percent Foreign Born		0.451*** (0.029)	0.319*** (0.032)	0.303*** (0.035)	0.285*** (0.046)
Log Population		-0.330 (0.223)	-0.853*** (0.206)	-0.544** (0.257)	-0.220 (0.365)
# Colleges Per Capita				94.11** (31.92)	144.2** (57.50)
College Tuition				0.000 (0.000)	0.000 (0.000)
State FE			Yes	Yes	Yes
Urban only					Yes
R^2	0.050	0.446	0.725	0.739	0.781
Observations	709	709	709	580	321

Notes: Columns (1) to (3) is the full sample of CZs which had at least 250 children with reported incomes as adults. Column (4) is the sample restricted to CZs with Title IV institutions with undergraduate students, that are degree offering. Column (5) is the sub-sample of urban CZs that overlap with Metropolitan Statistical Areas (MSAs). Each column reports coefficients from an OLS regression, with standard errors reported in the parenthesis. The dependent variable measures the college attendance rate among children aged between 18-21 years in the year 2000, who had parents ranked in the 25th percentile of the U.S. national income distribution, as measured by Chetty et al. (2014). The main explanatory variable, *Tech Measure*, is calculated as the portion of STEM workers out of total employed for each CZ (measured in percent). STEM workers include all those employed in Science, Technology, Engineering, and Mathematics careers as identified by the U.S. Bureau of labour Statistics (BLS); the workers are identified from Census 2000 by cross-referencing *occ1990* occupation codes to the BLS list. All models are weighted by the CZ share of national population in the year 2000.

*** Significant at the 1%
** Significant at the 5%
* Significant at the 10%

Table 4: 2SLS First Stage Estimates

	Dep Variable: $Tech\ Measure$ (in %)				
	(1)	(2)	(3)	(4)	(5)
$Tech\ Measure^{IV}$	0.707*** (0.022)	0.659*** (0.026)	0.707*** (0.033)	0.723*** (0.037)	0.772*** (0.051)
Precent Black		-0.001 (0.005)	-0.003 (0.008)	-0.001 (0.009)	0.004 (0.014)
Percent Foreign Born		-0.057*** (0.007)	-0.072*** (0.010)	-0.069*** (0.011)	-0.056*** (0.016)
Log Population		0.416*** (0.058)	0.431*** (0.065)	0.330*** (0.085)	0.086 (0.135)
# Colleges Per Capita				-11.77 (10.60)	-11.78 (20.82)
College Tuition				0.000 (0.000)	0.000 (0.000)
State FE			Yes	Yes	Yes
Urban only					Yes
R^2	0.583	0.620	0.723	0.723	0.715
F-statistics	991.0	287.7	31.67	24.44	11.85
Observations	709	709	709	580	321

Notes: Columns (1) to (3) is the full sample of CZs which had at least 250 children with reported incomes as adults. Column (4) is the sample restricted to CZs with Title IV institutions with undergraduate students, that are degree offering. Column (5) is the sub-sample of urban CZs that overlap with Metropolitan Statistical Areas (MSAs). Each column reports coefficients from a first-stage regression of the 2SLS estimation process, with standard errors reported in the parenthesis. The dependent variable, $Tech\ Measure$, is measured as the portion of STEM workers out of total employed for each CZ. The instrument, $Tech\ Measure^{IV}$, has been constructed by using industry-level STEM shares for each CZ in the base year 1970, and then estimating levels in the year 2000 by using national-level growth rates. All models are weighted by the CZ share of national population in the year 2000.
*** Significant at the 1%
** Significant at the 5%
* Significant at the 10%

Table 5: Absolute Intergenerational Mobility (Low-Income Rank) and Technology Measure in CZs, 2000: *2SLS estimates*

	Dep Variable: College Attendance Rate | Parental Income Rank at 25th Percentile				
	(1)	(2)	(3)	(4)	(5)
Tech Measure	1.462*** (0.153)	0.676*** (0.151)	0.582*** (0.139)	0.583*** (0.146)	0.616*** (0.167)
Percent Black		-0.154*** (0.020)	0.043* (0.025)	0.034 (0.027)	0.033 (0.036)
Percent Foreign Born		0.468*** (0.030)	0.338*** (0.032)	0.322*** (0.035)	0.300*** (0.042)
Log Population		-0.651** (0.253)	-1.094*** (0.227)	-0.766*** (0.269)	-0.387 (0.347)
# Colleges Per Capita				96.73*** (30.49)	149.6*** (52.54)
College Tuition				0.000 (0.000)	0.000 (0.000)
State FE			Yes	Yes	Yes
Urban only					Yes
R^2	0.001	0.439	0.723	0.736	0.778
Observations	709	709	709	580	321

Notes: Columns (1) to (3) is the full sample of CZs which had at least 250 children with reported incomes as adults. Column (4) is the sample restricted to CZs with Title IV institutions with undergraduate students, that are degree offering. Column (5) is the sub-sample of urban CZs that overlap with Metropolitan Statistical Areas (MSAs). Each column reports coefficients from a second-stage regression of the 2SLS estimation process, where the main explanatory variable, *Tech Measure*, has been predicted using the IV (Table 4 contains the corresponding first-stage regression results). Standard errors are reported in the parenthesis. The dependent variable measures the college attendance rate among children aged between 18-21 years in the year 2000, who had parents ranked in the 25th percentile of the U.S. national income distribution, as measured by Chetty et al. (2014). All models are weighted by the CZ share of national population in the year 2000.
*** Significant at the 1%
** Significant at the 5%
* Significant at the 10%

Table 6: Absolute Intergenerational Mobility (High-Income Rank) and Technology Measure in CZs, 2000

	Dep Variable: College Attendance Rate | Parental Income Rank at 75th Percentile				
	PANEL A: 2SLS estimates				
	(1)	(2)	(3)	(4)	(5)
Tech Measure	0.440*** (0.091)	0.143 (0.111)	0.246** (0.109)	0.254** (0.115)	0.299** (0.132)
Percent Black		-0.435*** (0.015)	-0.005 (0.020)	-0.014 (0.021)	-0.020 (0.028)
Percent Foreign Born		0.158*** (0.022)	0.109*** (0.025)	0.094*** (0.027)	0.072** (0.033)
Log Population		-0.086 (0.186)	-0.415** (0.178)	-0.146 (0.211)	0.105 (0.273)
# Colleges Per Capita				80.73*** (23.91)	110.9*** (41.43)
College Tuition				0.000 (0.000)	0.000 (0.000)
State FE			Yes	Yes	Yes
Urban only					Yes
R^2	0.001	0.146	0.520	0.536	0.587
	PANEL B: OLS estimates				
Tech Measure	0.187*** (0.069)	0.038 (0.076)	0.208*** (0.073)	0.214*** (0.078)	0.247** (0.098)
R^2	0.010	0.146	0.521	0.536	0.588
Observations	709	709	709	580	321

Notes: Columns (1) to (3) is the full sample of CZs which had at least 250 children with reported incomes as adults. Column (4) is the sample is restricted to CZs with Title IV institutions with undergraduate students, that are degree offering. Column (5) is the sub-sample of urban CZs that overlap with Metropolitan Statistical Areas (MSAs). The dependent variable measures the college attendance rate among children aged between 18-21 years in the year 2000, who had parents ranked in the 75th percentile of the U.S. national income distribution, as measured by Chetty et al. (2014). Each column in Panel A reports coefficients from a second-stage regression of the 2SLS estimation process, where the main explanatory variable, *Tech Measure*, has been predicted using the IV (Table 4 contains the corresponding first-stage regression results). Panel B provides the OLS coefficients for the technology measure for comparison, estimated by including the control variables that are indicated in the corresponding columns of Panel A. Standard errors are reported in the parenthesis. All models are weighted by the CZ share of national population in the year 2000.

*** Significant at the 1%

** Significant at the 5%

* Significant at the 10%

Table 7: Relative Intergenerational Mobility and Technology Measure in CZs, 2000

	Dep Variable: College Attendance Odds Ratio (25 Per./75 Per.) × 100				
	Panel A: 2SLS estimates				
	(1)	(2)	(3)	(4)	(5)
$Tech\ Measure$	1.611*** (0.150)	0.811*** (0.109)	0.598*** (0.125)	0.592*** (0.132)	0.598*** (0.152)
Percent Black		-0.171*** (0.019)	0.065*** (0.022)	0.059** (0.024)	0.065** (0.033)
Percent Foreign Born		0.484*** (0.028)	0.349*** (0.029)	0.339*** (0.031)	0.328*** (0.038)
Log Population		-0.694*** (0.235)	-1.047*** (0.204)	-0.820*** (0.243)	-0.521* (0.315)
# Colleges Per Capita				67.15** (27.53)	114.9** (47.71)
College Tuition				0.000 (0.000)	0.000 (0.000)
State FE			Yes	Yes	Yes
Urban only					Yes
R^2	0.001	0.501	0.771	0.7861	0.816
	Panel B: OLS estimates				
$Tech\ Measure$	0.799*** (0.111)	0.458*** (0.095)	0.299*** (0.093)	0.303*** (0.089)	0.341*** (0.112)
R^2	0.067	0.511	0.775	0.785	0.820
Observations	709	709	709	580	321

Notes: Columns (1) to (3) is the full sample of CZs which had at least 250 children with reported incomes as adults. Column (4) is the sample restricted to CZs with Title IV institutions with undergraduate students, that are degree offering. Column (5) is the sub-sample of urban CZs that overlap with Metropolitan Statistical Areas (MSAs). The dependent variable is the ratio of college attendance rate among children with parents ranked in the 25th percentile over parents ranked in the 75th, as measured by Chetty et al. (2014). Each column in Panel A reports coefficients from a second-stage regression of the 2SLS estimation process, where the main explanatory variable, $Tech\ Measure$, has been predicted using the IV (Table 4 contains the corresponding first-stage regression results). Panel B provides the OLS coefficients for the technology measure for comparison, estimated by including the control variables that are indicated in the corresponding columns of Panel A. Standard errors are reported in the parenthesis. All models are weighted by the CZ share of national population in the year 2000.

*** Significant at the 1%
** Significant at the 5%
* Significant at the 10%

Table 8: Labour Market Outcomes and Technology Measure in CZs, 2000

	Dep Variable: Fraction Skilled			*Dep Variable*: Skill Premium		
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: 2SLS estimates						
Tech Measure	2.943***	2.211***	1.739***	0.020***	0.007***	0.010***
	(0.106)	(0.126)	(0.114)	(0.001)	(0.001)	(0.000)
Percent Black		-0.048***	0.169***		0.001***	0.000
		(0.017)	(0.021)		(0.000)	(0.000)
Percent Foreign Born		0.085***	-0.147***		0.003***	0.003***
		(0.025)	(0.026)		(0.000)	(0.000)
Log Population		1.051***	1.773***		0.009***	0.007***
		(0.209)	(0.186)		(0.001)	(0.001)
State FE			Yes			Yes
R^2	0.576	0.659	0.835	0.213	0.687	0.894
PANEL B: OLS estimates						
Tech Measure	2.602***	2.150***	1.907***	0.014***	0.007***	0.010***
	(0.080)	(0.086)	(0.076)	(0.000)	(0.000)	(0.000)
R^2	0.586	0.660	0.837	0.257	0.687	0.894

Notes: $N = 741$ for columns (1) and (6) which is the total number of CZs in 2000. For columns (1) to (3), the dependent variable is *Fraction Skilled,* which measures the portion of full-time, full-year workers in a given CZ with at least one year of college education. For columns (4) to (6), the dependent variable is the *Skill Premium*, which is the coefficient of an education dummy from a wage regression estimated for individual CZs, where log hourly wages (full-time, full-year workers) have been regressed on an education dummy (some college or more), sex, two race categories (non-white, Hispanic), place of birth, and a quartic in age. Each column in Panel A reports coefficients from a second-stage regression of the 2SLS estimation process, where the main explanatory variable, *Tech Measure*, has been predicted using the IV (Table 4 contains the corresponding first-stage regression results). Panel B provides the OLS coefficients for the technology measure for comparison, estimated by including the control variables that are indicated in the corresponding columns of Panel A. Standard errors are reported in the parenthesis. All models are weighted by the CZ share of national population in the year 2000.

*** Significant at the 1%

** Significant at the 5%

* Significant at the 10%

Table 9: Changes in Labour Market Outcomes and Technology Levels in CZs, 1980-2000: *Stacked First Differences*

	PANEL A: 2SLS estimates					
	Dep Variable: Δ in Fraction Skilled			*Dep Variable*: Δ in Skill Premium		
	(1)	(2)	(3)	(4)	(5)	(6)
$\triangle$ *in Tech Measure*	0.519	1.493***	0.572	0.028***	0.007*	0.022***
	(0.484)	(0.563)	(0.759)	(0.004)	(0.004)	(0.005)
Percent Black$_{\text{-1}}$		0.002	0.003		-0.000***	-0.000**
		(0.011)	(0.020)		(0.000)	(0.000)
Percent Foreign Born$_{\text{-1}}$		-0.181***	-0.132***		0.001***	0.001***
		(0.024)	(0.032)		(0.000)	(0.000)
Log Population$_{\text{-1}}$		0.289**	0.233		0.005***	0.002*
		(0.141)	(0.161)		(0.000)	(0.001)
State FE			Yes			Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.020	0.077	0.170	0.118	0.366	0.442
	PANEL B: OLS estimates					
$\triangle$ *in Tech Measure*	0.823***	0.587***	0.401**	0.011***	0.010***	0.012***
	(0.158)	(0.161)	(0.170)	(0.001)	(0.001)	(0.001)
R^2	0.023	0.097	0.171	0.207	0.369	0.469

Notes: $N = 1,482$ (741 commuting zones × 2 time periods) for columns (1) to (6). For columns (1) to (3), the dependent variable is *Change in Fraction Skilled*, calculated as the difference in the portion of workers with some college education in a CZ between the years 1980-1990 and 1990-2000. For columns (4) to (6), the dependent variable is *Change in Skill Premium*, calculated as the difference in the education coefficient dummy from the CZ-level wage regressions between the years 1980-1990 and 1990-2000. The main explanatory variable for the regressions, $\triangle$ *in Tech Measure,* is calculated using a similar time-frame. All models include a dummy for the 1990-2000 time period. Other control variables have been measured at the CZ level using Census data at the start of decade. Each column in Panel A reports coefficients from a second-stage regression of the 2SLS estimation process, where the main explanatory variable, $\triangle$ *in Tech Measure,* has been predicted using an IV. The instrument has been constructed by using industry-level STEM data at a CZ in 1970 and then estimating levels for the years 1980, 1990 and 2000, by using national-level growth rates. The first stage coefficient estimates for the IV are 0.324 (s.e. 0.024) for model 1, 0.293 (s.e. 0.025) for model 2, and 0.259 (s.e. 0.030) for model 3. Panel B provides the OLS coefficients for comparison, estimated by including the control variables that are indicated in the corresponding columns of Panel A. Standard errors are reported in the parenthesis. All models are weighted by start of decade CZ share of national population.
*** Significant at the 1%
** Significant at the 5%
* Significant at the 10%

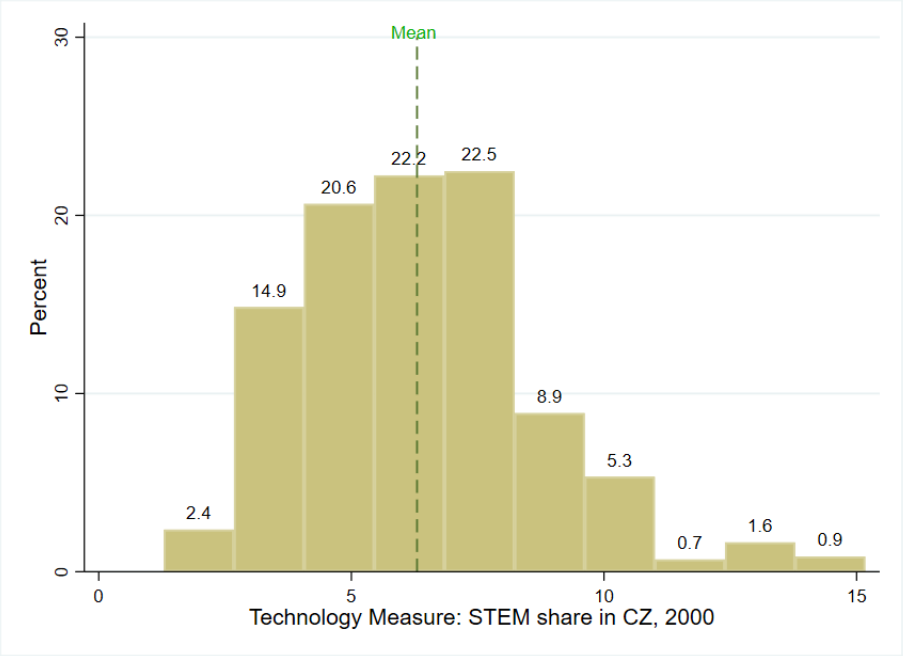

Figure 7: Distribution of CZs by Technology Measure in 2000

3 The Link between Skill-premium and Between-Group Inequality

3.1 Introduction

Labour market studies concerning changes in the earnings distribution have frequently looked at how skill differentials among workers can be a cause of wage differences. A particularly popular discourse is the skill-biased technical change (SBTC) narrative, which contends that the returns to being skilled get widened when technical change leads to the (relative) demand of skills growing faster than the supply of skills in the labour market (see Card & Dinardo, 2002; Goldin & Katz, 2008; Acemoglu & Autor, 2011, among others).[32] The empirical approach to measure the returns to skill is to typically segregate the working population into two skill groups based on their education profile- college equivalent workers and high school–equivalent workers- and then take the ratio of the (log) college-high school wage to calculate the *skill-premium*.[33]

The skill-premium has been the primary index used in several SBTC studies to understand how the returns to schooling have evolved over time in different countries. For example, Card and DiNardo (2002) use it to show how the wage-gap between college and high-school educated workers has moved in three distinct phases in the U.S. between 1970 and 1998 (falling in the 1970s, rising rapidly in the 1980s and relatively stable in the 1990s). However, in spite of its wide application in a field focused on examining income gaps, the skill-premium has limitations if one wants to use it to understand income inequality conditions more broadly. Technically, inequality measurement requires information on both within-group and between-group income differences. By its design, the skill-premium does not assess within-group differences. On the second dimension, the skill-premium describes between-group differences by only looking at the change in the wage gap; this creates a limitation as it is possible to have both the skill-premium and the portion of skilled workers increasing in the canonical SBTC model (as illustrated in Figure 1, and discussed in the following section). As a consequence, even in the context of between-group inequality, the story told by the skill-premium might not match the story being

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[32] The idea that technological developments increase the demand for skills is primarily based on the pioneering work of Tinbergen (1974).

[33] The process of how the skill premium is theoretically derived in the SBTC model and then empirically assessed is described in detail in a number of papers, such as Card & DiNardo (2002), Acemoglu & Autor (2011) etc.

told by standard inequality indices like the Gini, Theil and the 90-10 wage-gap, which respond to changes in the population shares.

When one considers the large attention that the issue of inequality has received in labour economics, it is perhaps surprising to realize that the link between the skill-premium and other measures of between-group inequality has not been analyzed in detail. The purpose of this paper is address this gap. Specifically, it analyzes how a change in the skill-premium which is accompanied by a change in the skill share would impact between-group inequality as assessed by traditional inequality measures like the Gini. For a theoretical understanding, I start by constructing a population-share based inequality index- the Gini coefficient (e.g. Atkinson, 1970; Anand, 1983)- for an SBTC economy, by grouping individuals based on their skill profile (high-skilled and low-skilled). The constructed 2-group Gini measure is shown to be a function of the skill premium, along with the population shares of the two skill groups. The measure is used for an exercise in comparative statics, where I specifically focus on finding conditions (if any) under which an increase in the skill-premium can contribute to reducing between-group inequality.

I show that if an economy has at least half of the workers being skilled at the outset, and the portion of skilled workers is increasing with the skill-premium- i.e. both the demand and supply of skills are increasing, with demand rising faster than supply- then the Gini may fall even as the skill-premium rises. This condition makes intuitive sense. A simple way to think of between-group inequality (in a 2 group case) would be if we find that one group has a higher share of income than their population share (e.g. see Conceicao & Ferreira, 2000). Thus, a rising skill-premium coupled with an increase in the portion of skilled workers can reduce between-group inequality, as that can reduce the discrepancy between the population share and the income share of each skill group (i.e. income and population share of the skilled group goes up, income and population share of the unskilled group goes down). The condition also implies that it is theoretically possible for the skill-premium's contribution to between-group inequality to change over time. When the portion of skilled workers in the economy is low, an increase in the skill-premium would increase between-group inequality; once some threshold is crossed, the relationship can become reversed.

I next go to the data to find evidence for this insight. The objective is to see how a rising skill-premium has interacted with a growing share of "college-educated" workers in the U.S. to impact between-group inequality, as measured by the Gini coefficient. Using labour market data from the March Current Population Survey (CPS) from 1980 to 2018, I calculate the yearly skill-premium for full-time, full-year (FTFY) workers by running a standard wage regression with an education dummy for workers with at least some college experience (and appropriate demographic controls). The Gini is then calculated for the same group of workers by using income shares and sample shares of “no college” vs. “college” workers.

Between 1980 to 2018, it is seen that the share of workers with at least some college education in the FTFY sample grew 31 percentage points (from 35% to 66%), while the skill-premium almost doubled (from 0.23 log points in 1980 to 0.45 in 2018). The impact of these increases has been that it has caused the 2-group Gini to move in a concave shape. From 1980-2005, the skill-premium and the Gini consistently increased together, with a strong positive correlation between them (0.96). However, since 2005, the indices have started moving in opposite directions; while the skill premium increased by 6%, the percentage change in the 2-group Gini was -14% (for this period, the correlation is -0.61). Trends over shorter time-intervals also support how the skill-premium and the Gini have not moved congurently since 2005: considering 3-year intervals between 2005-2018, it is seen that the skill-premium increased in 3 of the 4 intervals, while the Gini fell across all 4 intervals.

I also calculate a Gini based on increased skill-groupings, where the FTFY sample is segregated into four skill groups- “less than high-school”, “high-school”, “some college” and “college or higher”. The 4-group measure accounts for some level of within-group inequality among college and non-college workers; even then, it is seen that the 4-group Gini has reduced in comparison to the skill-premium since 2005, going down by 3%. A robustness check done using an alternate measure of inequality, the Theil Index, also reveals similar patterns- after growing together with the skill-premium from 1980 to 2005, the 2-group Theil and the 4-group Theil is found to have decreased by 16% and 4% respectively between 2005-2018. The results in conjunction therefore support the insight that, with a growing skill supply, the impact of the skill-premium to between-group inequality can change over time.

Through these findings, the paper makes two important contributions. One is related to the theoretical workings of the SBTC model- while it is known how the demand and supply of relative skills interact to determine the skill-premium, the work here extends this understanding to show how this can be linked to between-group inequality. The second is to show that the link between the skill-premium and standard measures of between-group inequality has fundamentally changed over the years. A success point of the SBTC model was that it effectively explained the large rise in the college premium in the 1980s following a decrease in the supply of skilled workers in the earlier decade (see Katz & Murphy, 1992). At that point, when the proportion of skilled workers in the population was relatively lower, the rise in the college premium coincided with an increase in between-group inequality. Consequently, researchers could take the information of a growing skill-premium to conclude that inequality conditions were becoming worse. However, with a large portion of workers being skilled today (almost two-thirds of FTFY workers have college experience), the relationship between the skill-premium and between-group inequality has reversed. Thus, the skill-premium today is only useful to gauge the difference in the average wage between the two skill groups; any connection to inequality conditions has to be cautiously made.

The rest of the chapter is organized as follows. Section 3.2 describes a theoretical link between the skill-premium and the Gini measure within the context of the SBTC model. Section 3.3 describes the data used in the paper, while section 3.4 discusses the empirical findings which provide evidence for the theoretical work. Section 3.5 then concludes the chapter.

3.2 Theoretical Link

3.2.1 Skill-Premium & Between-Group Inequality

In the canonical SBTC model, the skill-premium is determined by the race between demand and supply of relative skills in the labour market- the premium increases when demand changes faster than supply. To illustrate how the skill-premium could move differently from standard, population-share based inequality indices, consider the two scenarios shown in Figure 8. In Figure 8(a), the skill-premium has increased following an increase in the relative demand of skills, but the supply of relative skills has stayed constant. In this scenario, where the population shares of the two groups have remained the same, but the income share of the skilled group has gone up, it is clear that the rising skill-premium must lead to a worsening of between-group inequality. In Figure 8(b), both the relative demand and supply of skills have increased, with demand growing more; the outcome is that skilled workers are earning more, but the economy also has a greater share of skilled workers. While the skill-premium still shows a widening of the income gap, the change in the inequality indices would be indeterminate- they could rise or fall, depending on how the skill-share has changed. As a consequence, there is no definite way of knowing whether the increase in the skill-premium is associated with an increase in between-group inequality or not.

3.2.2 Constructing a SBTC Gini

Consider an economy which has the following SBTC features. There are workers of two skill-types in the economy: high-skilled and low-skilled. The portions of each group in the total population is considered to be h and $(1-h)$ respectively. The (per hour) skilled wage rate is w_H while the unskilled wage is w_L. The unskilled wage rate is normalized to 1, so that the skilled wage is $w_H/w_L = \omega$, i.e. the wage ratio between skilled and unskilled labour, or the skill-premium. A standard assumption followed is that skilled workers can choose whether to work as skilled or unskilled employees, implying that the skilled wage can never fall below the unskilled wage (e.g. Mokherjee & Napel, 2006); this means that $\omega > 1$. I assume all agents make identical work choices, each supplying l hours of labour (thus, l can be set to 1).

Following this exposition, the total income in the economy is $\omega h + (1-h)$, and the fraction of income earned by each group is:

$$\textit{skilled group} \Rightarrow \quad \frac{\omega h}{\omega h + (1-h)}$$

$$\textit{unskilled group} \Rightarrow \quad \frac{(1-h)}{\omega h + (1-h)}$$

To examine the dispersion of the distribution of income between the two skill groups, I choose the Gini coefficient which is one of the most commonly used inequality indices. I follow the geometric approach of using the Lorenz curve to calculate the Gini coefficient: the coefficient is equal to the area below the diagonal of perfect equality, minus the area under the Lorenz Curve. As the focus is to the examine the income distribution between two discrete population groups whose income and population shares are known, I estimate the Lorenz curve using a technique of linear interpolation as shown by Anand (1983).

Suppose there are n groups, who are labeled in a non-descending order of (average) income: $y_1 \leq y_2 .... \leq y_n$. Let F_i be the cumulative population share and θ_i be the cumulative income share of group i, with $F_0 = \theta_0 = 0$. The Gini coefficient is then given by:

$$G = 1 - \sum_{i=0}^{n-1} (F_{i+1} - F_i)(\theta_{i+1} + \theta_i) \tag{3.1}$$

For the SBTC economy, with the unskilled group's income being lower than the skilled group, the Gini can be estimated as:

$$G = 1 - \left[\frac{(1-h)^2}{\omega h + 1 - h} + h \left(1 + \frac{1-h}{\omega h + 1 - h} \right) \right]$$

$$G = \frac{(h - h^2)(\omega - 1)}{\omega h + 1 - h} \tag{3.2}$$

Figure 9 illustrates the Lorenz Curve of the SBTC economy, by plotting the cumulative population shares of the two skill groups on the x-axis and their respective income shares on the y-axis. The line segment ABC shows the Lorenz Curve, while AC represents the diagonal of equality.

The Gini measure in Equation (3.2) is a function of the skill-premium, ω, and the portion of skilled workers, h, in the economy. It can be used to examine how changes in the skill-premium will impact the dispersion of the income distribution between the two skill groups. In the comparative statics exercise below, I specifically focus on finding conditions under which an increase in the skill-premium can cause the Gini to fall.

3.2.3 Comparative Statics

In the canonical SBTC model, the skill-premium is linked to the relative supply of skills and to the relative technology level, which drives the relative demand of skills. Changes in these factors happen exogenously in the standard model. Here, I will analyze the effects of an exogenous shock z, which may operate via changes in either supply or demand of relative skills, or both (as discussed further below). Depending on how z is impacting the demand and supply of relative skills, the wage premium and the portion of skilled workers in the economy will be determined as key equilibrium outcomes in the model; this implies that we have $\omega(z)$ and $h(z)$.

Consequently, the Gini measure becomes a function of z, or $G(\omega(z), h(z))$. The impact on G from a change in z is then given by the total derivative in Equation (3.3):

$$\frac{\partial G(\omega(z), h(z))}{\partial z} = \underbrace{\frac{\partial G}{\partial \omega}}_{a} \underbrace{\frac{\partial \omega}{\partial z}}_{b} + \underbrace{\frac{\partial G}{\partial h}}_{c} \underbrace{\frac{\partial h}{\partial z}}_{d} \tag{3.3}$$

Using Equation (3.2), the derivative $\partial G/\partial \omega$ is found to be positive:

$$\frac{\partial G}{\partial \omega} = \frac{h(1-h)}{(\omega h + 1 - h)} > 0$$

This means that the sign of $(a \times b)$ is going to depend on $\partial \omega/\partial z$. Assume that $\partial \omega/\partial z \neq 0$; an immediate result that follows from (3.3) then is that if $\partial h/\partial z = 0$ (i.e. the portion of skilled workers in the economy has not changed), then the skill-premium and the Gini will always move in the same direction.[34]

Suppose that the skill premium in the economy is increasing- i.e. $\partial \omega/\partial z > 0$, and $\partial h/\partial z \neq 0$. What are the conditions under which the Gini might fall? With $(a \times b) > 0$, this means that a necessary condition for the total derivative to be negative is that $(c \times d) < 0$. This requires that the partials $\partial G/\partial h$ and $\partial h/\partial z$ must have opposite signs.

The partial $\partial G/\partial h$ is calculated as:

$$\frac{\partial G}{\partial h} = \frac{(\omega - 1)\left[(1-2h)(\omega h + 1 - h) - (\omega - 1)(h - h^2)\right]}{(\omega h + 1 - h)} \tag{3.4}$$

For the expression in (3.4) to be negative, the condition required is $h > 0.5$; for the expression to be positive, the condition required is for h to be as small as possible (with a maximum value of 0.5).[35] From these findings, two sets of necessary conditions can be identified which can cause the Gini to fall when the skill-premium increases:

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[34] This is the scenario that was described in Figure 8(a), for the case of labour supply being perfectly inelastic.

[35] The partial derivative $\partial G/\partial h > 0$ when the following condition holds: $\frac{(1-2h)}{h^2} > (\omega - 1)$; this condition will hold when h is small, and at least smaller than 0.5.

1. $\partial G/\partial h < 0$ and $\partial h/\partial z > 0$ the economy needs to have at least half of the workers being skilled at the outset, and the portion of skilled workers has to be growing in reaction to the shock that increases the skill premium. This would need both the demand and supply of relative skills to be increasing, with demand rising faster than supply (as in Figure 8(b)).

2. $\partial G/\partial h > 0$ and $\partial h/\partial z < 0$: the economy needs to have a low portion of skilled workers at the outset, and the portion of skilled workers has to be falling as the skill-premium is rising. This would need the supply of relative skills to be falling while the demand of skills is rising (or constant).

Out of these results, set (1) is the more relevant case to focus on, as the data shows that the portion of skilled workers has been generally growing in the U.S. in the past 40 years. What it suggests is that the impact of the skill-premium on between-group inequality in an economy can change over time. When the portion of skilled workers is low (below half), then an increase in the skill-premium will always increase between-group inequality; when the skill-share crosses a level, then the Gini can fall, even with a rising skill-premium.

3.3 Data

3.3.1 Data Source

The focus of the empirical work is to see if trends in the skill-premium, the portion of skilled workers, and the inequality measures as observed in the U.S. are moving in the pattern as suggested by the theoretical work. To observe these trends, I use labour market data from the March Current Population Survey (March CPS). The data is taken from the IPUMS-CPS database (Flood, King, Rodgers, Ruggles & Warren, 2020), covering the years 1980 to 2018. When selecting the sample, I focus on only full-time, full-year workers, aged 18-64, who identify themselves as working for wages or salary and have reported a non-zero annual income (workers working for the government and the military are excluded). Full-time, full-year workers are considered to be those who have worked at least 35 hours per week and forty or more weeks in the previous year.[36]

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[36] The reason for focusing on FTFY workers is to have some degree of standardization when it comes to labour-hour choices, as followed in the theoretical work.

The indicators of the study are all constructed from the hourly wage data and the education profile of the sample. Before construction, the (nominal) annual earnings of each year are adjusted to constant 1999 dollars using the CPI99 variable from IPUMS. Hourly wages are then calculated after dividing annual earnings with the amount of hours worked in a year (hours worked per week multiplied by numbers of weeks worked in the year). The education background of the worker is determined by looking at the years of schooling reported.

3.3.2 Indices

Skill-Premium

The yearly skill-premium is estimated by running the following wage-regression:

$$log(w_{j,t}) = \alpha_t + \beta_t(educd_{j,t}) + \theta_t X_{j,t} + e_{j,t} \tag{3.5}$$

Using information for each FTFY worker, j for the year, t , the regression in (3.5) is run year-by-year. The log of hourly wage ($w_{j,t}$) is regressed on an education dummy ($educd_{j,t}$), which is set to 1 for respondents who have attended at least 1 year of college (i.e. some college or more). A vector of control variables ($X_{j,t}$) that include gender, two race/ethnicity categories (Black, Hispanic), and a quartic in age are included in the regression to control for demographic differences among the workers. The coefficient of the education variable from this regression analysis is then used to measure the skill-premium at the country level for a given year.

Gini Coefficient

The focus of the study is to look at inequality between groups of individuals, with the criterion of grouping being their skill (education) level. Two types of Gini measures are constructed, one with the sample being grouped into two skill categories (2-group Gini) and the other with the sample being grouped into four skill categories (4-group Gini). The 2-group Gini follows the skill-segregation approach of the skill-premium, by segregating FTFY workers into a “no-college” experience group (education level of high-school or lower) and a “some-college” experience group (education level of at least 1 year of college). For the 4-group Gini, the workers are segregated into: "less than high-school" (those with less than Grade 12 education), "high-school" (those who have completed high-school), "some college experience" (those who have attended some college but without a degree) and "college or higher" (those with a college degree or higher).[37]

After the groups are created, their respective income shares (using hourly wage data) and size shares are computed from the CPS data. Equation (3.1) is then used to estimate the 2-group and the 4-group Gini coefficients.

Theil Index

For robustness check, I make use of the between-group component of the Theil Index (e.g. Conceicao & Ferreira, 2000) which can be calculated as:[38]

$$T = \sum_{i=0}^{n} y_n ln\left(\frac{\bar{x_n}}{\bar{x}}\right) \tag{3.6}$$

where y_n is the n-th group's income share out of total income of the sample, $\bar{x_n}$ is the mean income (i.e. mean hourly wage) of the group, and $\bar{x}$ is the mean income of the sample. The groups are again created based on the skill profile of the FTFY sample, following the same segregation strategy as the Gini, leading to the construction of a 2-group Theil and a 4-group Theil.

In the following section, I discuss the trends of the skill-premium and the inequality indices as observed for U.S. FTFY workers between 1980-2018. When reading the results, it is worth noting that the inequality indices which I am using- Gini and the Theil- are objective measures of inequality, and not normative measures (as described by Sen, 1997).

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[37] It is technically possible to use even more skill groups to construct the Gini. However, the skill-premium by design analyzes income differences between two skill groups only. For the purpose of the study therefore, it is more useful to construct the Gini with a skill-grouping approach which matches (or is close to) the skill-premium's approach. Moreover, even if we create more additional groups in the lower and higher end of the skill spectrum, the portion of FTFY workers in these categories become very small. For example, a category like "less than 5th Grade schooling" has less than 1% of the sample population; a category like "more than college degree" has around 4%.

[38] The standard Theil Entropy Index (Theil, 1967) can be decomposed into two additive parts of between-group and within-group inequality (see Liao, 2016). However, as the focus is to understand how the skill-premium impacts the income distribution between the skill groups, I focus on the first component.

Objective measures are designed to provide an assessment of inequality purely on the basis of certain statistics which capture the variation of income among individuals or groups. Therefore, the discussions which follow (and any conclusions being subsequently drawn) are solely based on how these statistics behave; any ethical or social welfare implications has been left out.

3.4 Empirical Findings

3.4.1 Skill-Premium and Portion of Skilled Workers

Figure 10 traces the yearly skill-premium (as estimated by Equation 3.5) among FTFY workers in the U.S. between the years 1980 and 2018. The initial trend is similar to the findings of Card & DiNardo (2002) as discussed earlier, with the premium increasing 51% between 1980 to 1990. The rise for the next two decades are slower, with the premium growing 16% for the second decade, and 12% for the third decade. Between 2010 and 2018, the premium has remained more stable, increasing around 2%.

For the Gini measure to fall with an increasing skill-premium, the necessary condition is that the portion of skilled workers has to increase. Figure 11 traces how the portion of skilled workers- measured as workers with some college education- have grown among U.S. FTFY workers year on year, increasing from 35% in 1980 to 66% in 2018. Combined with the increasing skill-premium, this has meant that the income shares by worker's education have significantly changed between 1980 and 2018. As shown in Figure 12, where the top 2 bars represent the "skilled group", workers with some college education have increased their share of total wage income from 42% in 1980 to 76% in 2018.

3.4.2 Skill-Premium and Inequality Indices

I plot the trends of the skill-premium and the Gini coefficients (2-group and 4-group) in Figure 13. From the plot, what stands out is that after increasing together with the skill-premium for the first two decades, both the Gini lines appear to take a dip from 2005 onward. Specifically, between the period of 2005 to 2018, the percentage change in the 2-group Gini is -14% while for the 4-group Gini, it is -3%; in the same period, the skill-premium is found to have increased 6%.

The correlation plots presented in the panel diagram in Figure 14 also show how the relationships between the skill-premium and the Gini measures have changed over time. The two diagrams in the first row of the panel show the correlations between the skill-premium and the 2-group Gini, while the two diagrams in the second row show the correlations between the skill-preium and the 4-group Gini. The correlations are plotted by splitting the time frame in two windows- the first being 1980-2005 (diagrams on the LHS of the panel), and the second being 2005-2018 (diagrams on the RHS of the panel). For the time period of 1980 to 2005, it is observed that the skill-premium had a (almost) perfect positive relationship with both the Gini coefficients, with correlation coefficients being close to 1. When considering the second time window of 2005 to 2018, the pattern now becomes inconsistent, and the correlations all become negative. The coefficient between the skill-premium and 2-group Gini is found to be -0.61, while with the 4-group Gini, it is -0.28.

Investigating changes between shorter time intervals also reveal how the Gini measures have more or less consistently fallen since 2005 (data for all indices are presented in Table 10). Considering changes across 3-year intervals between 2006 and 2018, it is seen that the percentage change in the 2-group Gini was negative in all four intervals, while for the 4-group Gini, it was negative in three out of the four intervals; conversely, the skill-premium is found to have decreased in only one of the four intervals.

For robustness check, trends between the skill-premium and the Theil indices (2-group and 4-group) are also investigated. The same downward trends are also evident in the Theil plot lines from 2005 onward (Figure 15); specifically, in the critical period of 2005-2018, the percentage change in the 2-group Theil and the 4-group Theil is found to be -16% and -4% respectively. The correlation plots (Figure 16) also emphasize these trends, with all the coefficients being strongly positive within the first window of 1980 to 2005, and being negative in the second window of 2005 to 2018. The analysis using 3-year intervals also show that the direction of changes in the Theil measures are consistent with the downward changes as found in the Gini measures, with the 2-group Theil going down in all four intervals, and the 4-group Theil having decreased in three of the four intervals.

Overall, these trends provide evidence for the theoretical insight that was found earlier: if the portion of skilled workers is growing, the impact of the skill-premium on between-group inequality can change over time.

3.5 Conclusion

In the class of explanations about changes to the wage structure, an extensive amount of work has been done following the SBTC hypothesis which contends that wage-gap between skilled and unskilled workers is determined by the race between technology (which drives the demand of skills) and the supply of skills. The goal of these studies have been to enhance our understanding about the nature and causes of wage inequality. However, the index which these studies have commonly used as a summary measure of inequality- the *skill-premium*- is not a "robust" inequality measure by itself, as a) it is not designed to capture within-group income differences and b) when describing the between-group income difference, it might not fully account for changes in the skill-share of the population.

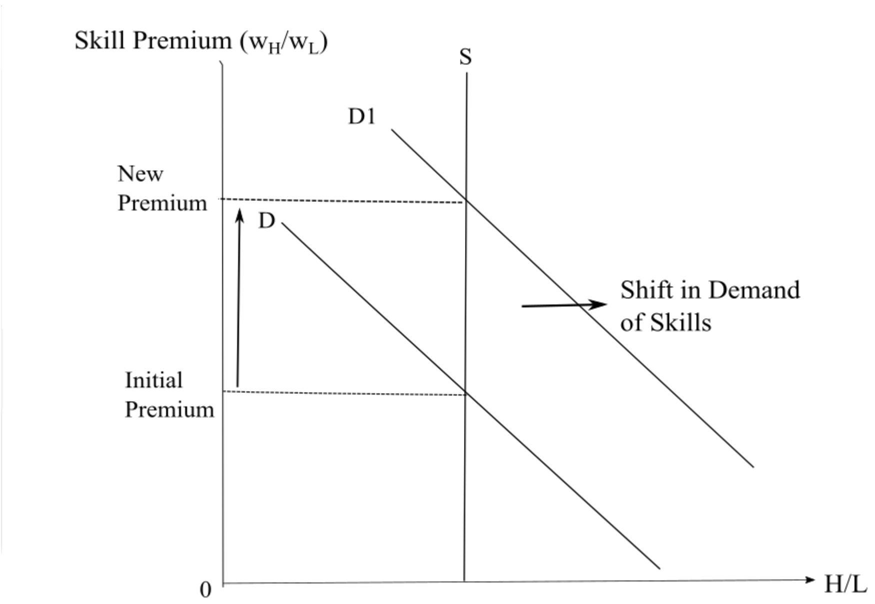
To address this gap, this paper analyzes how a change in the skill-premium which is accompanied by a change in the skill share would impact between-group inequality among skilled and unskilled workers. A theoretical exercise first shows that if an economy has at least half of its workers as skilled at the outset, and the portion of skilled workers is increasing with the skill-premium, then between-group inequality, as measured using the Gini coefficient, could potentially fall. An empirical investigation is then done to see how a rising skill-premium has interacted with a growing share of "college-educated" workers in the U.S. to impact between-group inequality among FTFY workers. Two types of inequality indices- the Gini and the Theil- are calculated by segregating the FTFY worker sample into two and four skill categories. The notable feature of these trends is that after growing together with the skill-premium from 1980 to 2005, all the inequality indices have moved in the opposite direction- specifically, between 2005 and 2018, the 2-group Gini and the 2-group Theil have decreased 14% and 16% respectively, while the skill-premium has increased 6% (the 4-group Gini and the 4-group Theil have also fallen, by 3% and 4% respectively). The correlation between the skill-premium and the inequality indices also change significantly- before 2005, there is an almost perfect positive correlation between the indices, while after 2005, the correlation becomes negative and no consistent pattern can be seen.

The consequential result of the paper can thus be summarized as follows: the contribution of the skill-premium to between-group inequality can change over time, as the skill-share in the population is growing. When the portion of skilled workers in the economy is below a threshold, the skill-premium moves in the same direction as between-group inequality; once the skill-share grows and crosses a point, the relationship between skill-premium and between-group inequality reverses. The important implication of this finding is over recent years, the skill-premium has become an inadequate index of overall *between-group inequality*, given the high share of skilled workers in the U.S. economy. On top of this, it is worth highlighting again that the skill-premium also ignores *within-group inequality*- i.e. the inequality due to the variability of income within each skill group. For a proper analysis of total inequality in a society, one needs to do an aggregation of *between-inequality* and *within-inequality.* Given the limitations of the skill-premium in both these domains, the paper advises that the application of the skill-premium as a tool for the empirical analysis of wage inequality should be carefully reviewed.

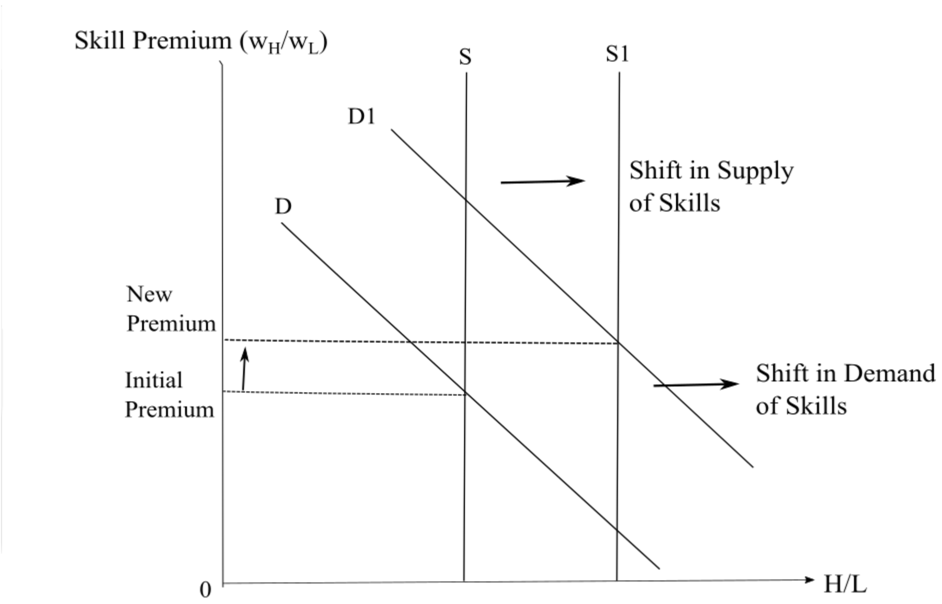
Table 10: Change in Skill-Premium and Inequality Indices

	Percentage Change over Interval				
	Skill-Premium	Gini Coefficient		Theil Index	
Intervals		*2-Group*	*4-Group*	*2-Group*	*4-Group*
1980-1990	51%	36%	38%	74%	76%
1990-2000	16%	21%	30%	50%	66%
2000-2010	12%	2%	9%	10%	19%
2010-2018	2%	-10%	-3%	-13%	-4%
2005-2018	**6%**	**-14%**	**-3%**	**-16%**	**-4%**
2000-2003	4%	7%	9%	15%	20%
2003-2006	3%	1%	2%	3%	6%
2006-2009	5%	-5%	-1%	-6%	-1%
2009-2012	0%	-6%	-4%	-9%	-8%
2012-2015	-3%	-3%	-3%	-4%	-6%
2015-2018	4%	-2%	1%	-1%	5%

Notes: The indices presented are calculated using wage earnings and education data for a sample of U.S. full-time, full-year (FTFY) workers, with data source being the March CPS. The yearly *skill-premium* is the coefficient of an education dummy from a wage regression estimated for individual workers, where log hourly wages have been regressed on an education dummy (some college or more), sex, two race categories (non-white, Hispanic), and a quartic in age. To estimate the group-based Gini coefficients and the Theil indices, the workers are segregated on the basis on their education profile. For the 2-group indices, the workers are split into a "no-college" experience group (education level of high-school or lower) and a "some-college" experience group (education level of at least 1 year of college). For the 4-group indices, the workers are segregated into: "less than high-school" (those with less than Grade 12 education), "high-school" (those who have completed high-school), "some college experience" (those who have attended some college but without a degree) and "college or higher" (those with a college degree or higher). The numbers in the table capture the percentage change in the indices over the designated time intervals.



(a) Demand of Relative Skills Increasing but Supply Fixed:
increase in skill-premium but portion of skilled workers unchanged



(b) Demand and Supply of Relative Skills Both Increasing:
increase in both skill-premium and portion of skilled workers

Figure 8: Skill-Premium Determination in the SBTC model

Notes: The x-axis shows the relative portion of skilled workers in the economy, given as the ratio of high-skilled workers (H) over low-skilled workers (L). The y-axis shows the skill-premium or the relative wage of skilled labour, given as the ratio of the high-skilled wage (w_H) over low-skilled wage (w_L).

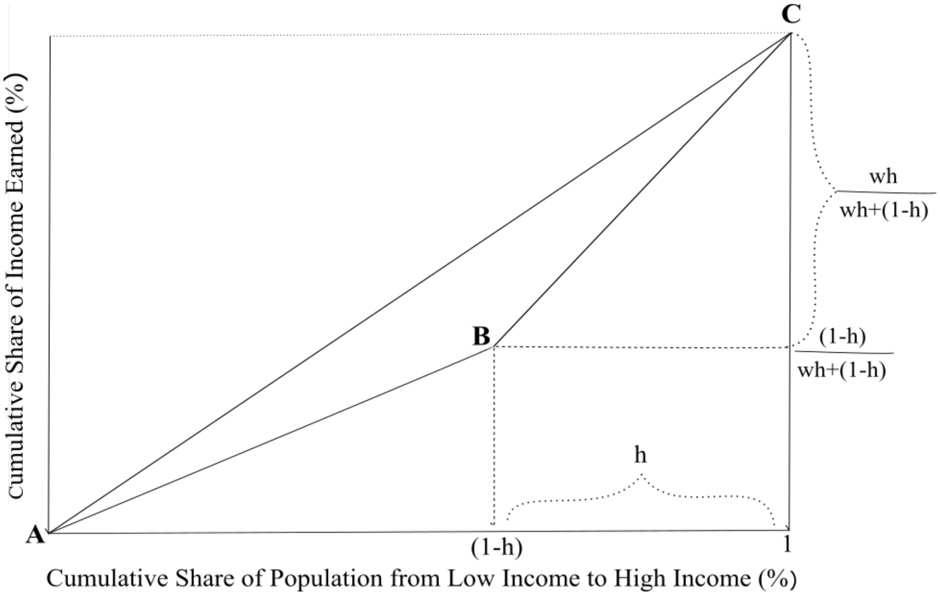


Figure 9: The Lorenz Curve for the SBTC Model with Two Skill Groups

Notes: The Lorenz Curve has been constructed considering that the economy has h portion of skilled workers, and $(1-h)$ portion of unskilled workers. The unskilled wage has been normalized to 1, so that the skilled wage equals $w_H/w_L = \omega$, i.e. the skill-premium. The line segment ABC shows the Lorenz Curve, while AC represents the diagonal of equality.

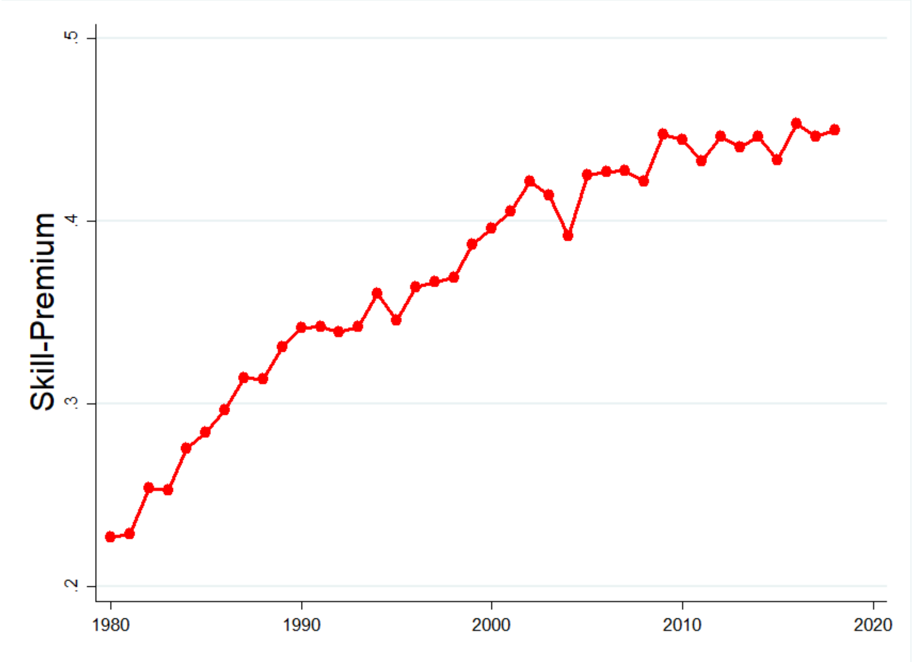


Figure 10: Skill-Premium for U.S. FTFY workers, 1980-2018

Notes: The yearly *skill-premium* is the coefficient of an education dummy from a wage regression estimated for individual workers from the FTFY sample, where log hourly wages have been regressed on an education dummy (some college or more), sex, two race categories (non-white, Hispanic), and a quartic in age.

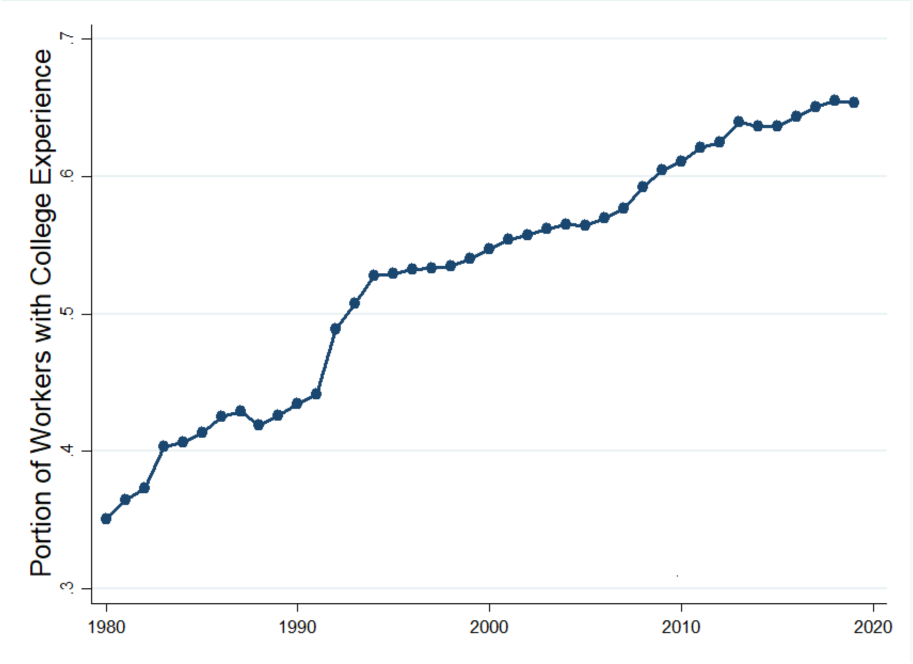


Figure 11: Portion of U.S. FTFY Workers with Some College Experience, 1980-2018

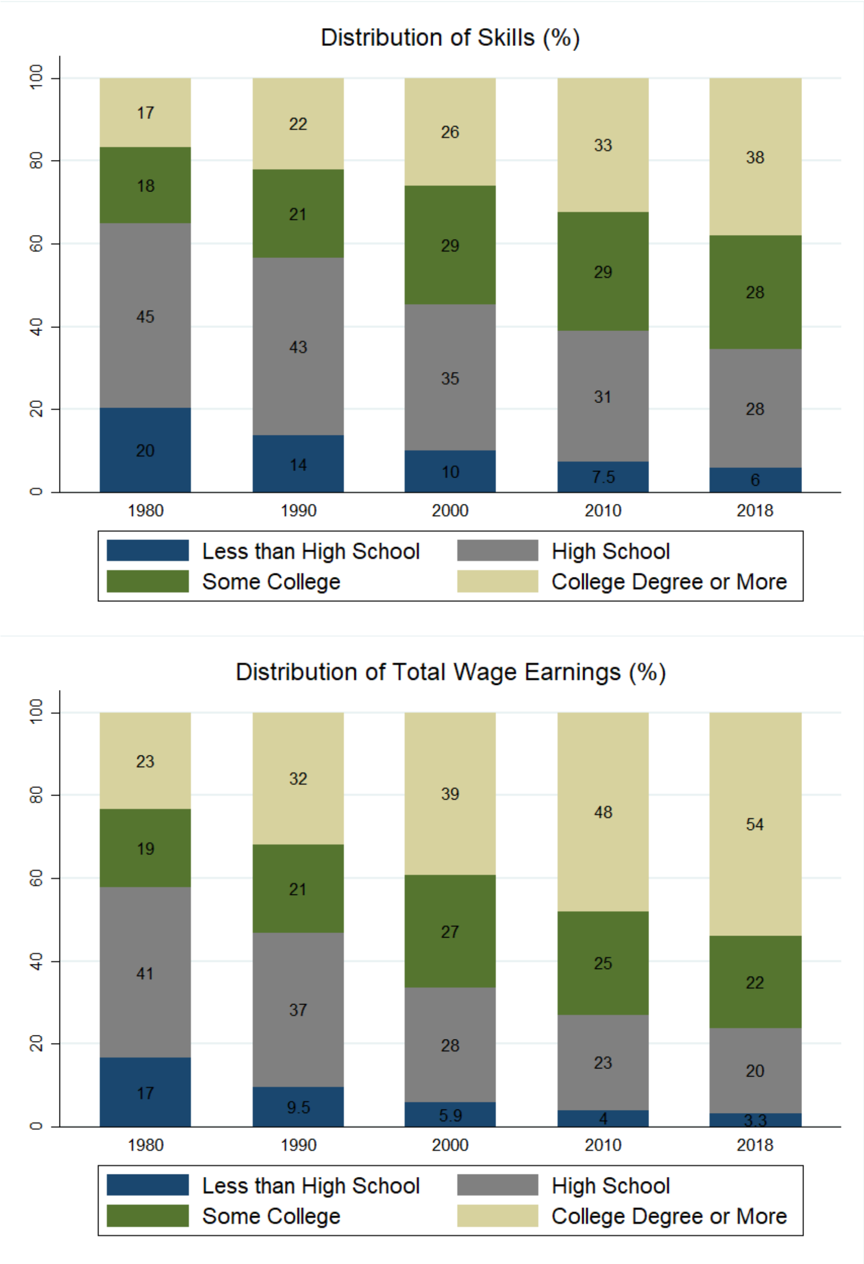


Figure 12: Distribution of U.S. FTFY workers by Education Level and Total Wage Earnings

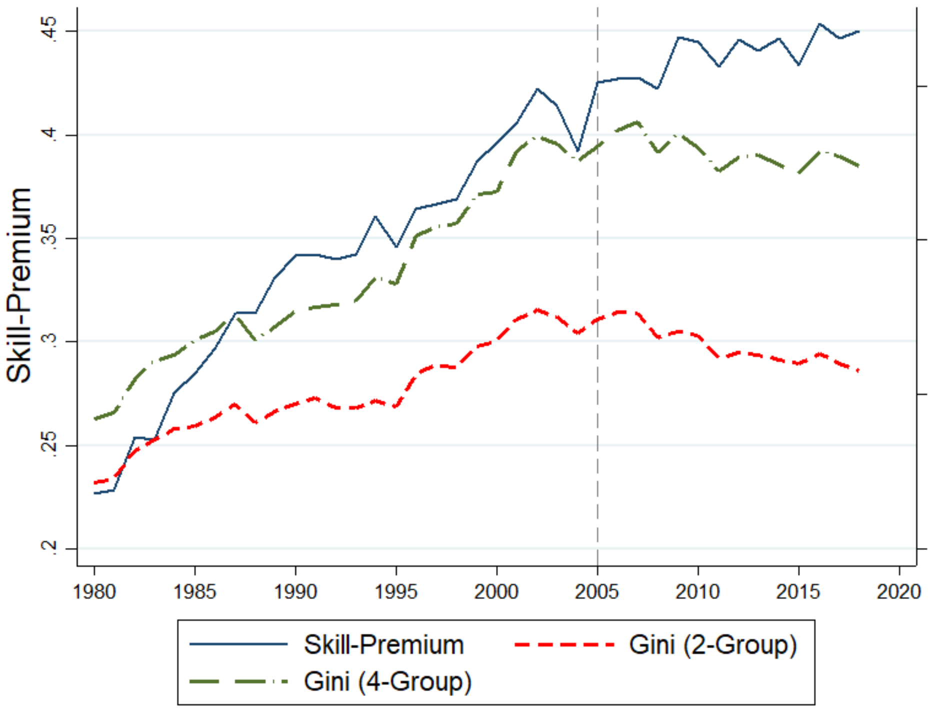
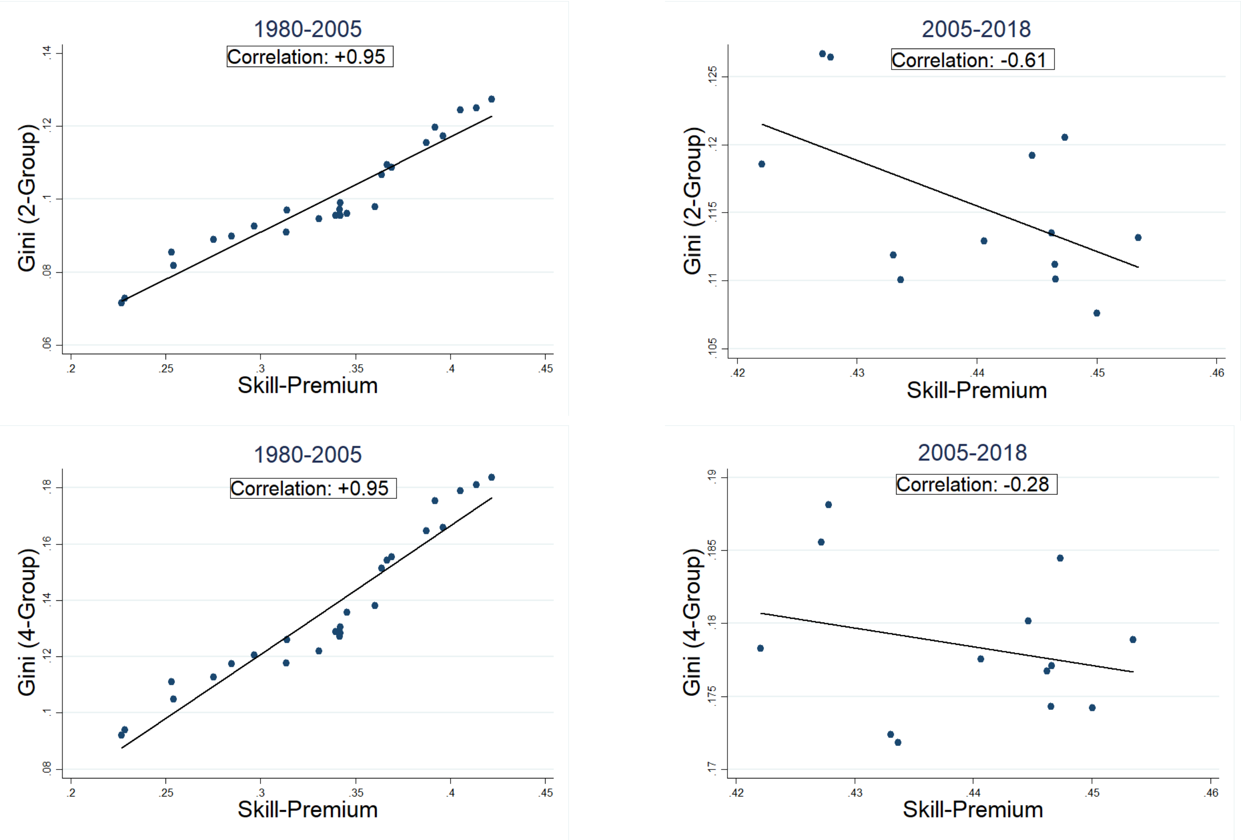


Figure 13: Annual Trends: Skill-Premium and Gini Coefficients for U.S. FTFY workers, 1980-2018

Notes: The yearly *skill-premium* is the coefficient of an education dummy from a wage regression estimated for individual workers from the FTFY sample, where log hourly wages have been regressed on an education dummy (some college or more), sex, two race categories (non-white, Hispanic), and a quartic in age. To estimate the 2-group Gini, the workers are split into a "no-college" experience group (education level of high-school or lower) and a "some-college" experience group (education level of at least 1 year of college). For the 4-group Gini, the workers are segregated into: "less than high-school" (those with less than Grade 12 education), "high-school" (those who have completed high-school), "some college experience" (those who have attended some college but without a degree) and "college or higher" (those with a college degree or higher).



1980-2005

2005-2018

1980-2005

2005-2018

Figure 14: Correlation: Gini Coefficients and Skill-Premium, 1980-2005 vs. 2005-2018

Notes: The panel diagram shows how the correlations between the skill-premium and the Gini indices (2-group and 4-group) have changed over two windows: 1980 to 2005, compared to 2005 to 2018. The diagrams in the first row of the panel show the correlation between the skill-premium and the 2-group Gini over the two designated time periods, while the diagrams in the second row show the correlation between the skill-premium and the 4-group Gini.

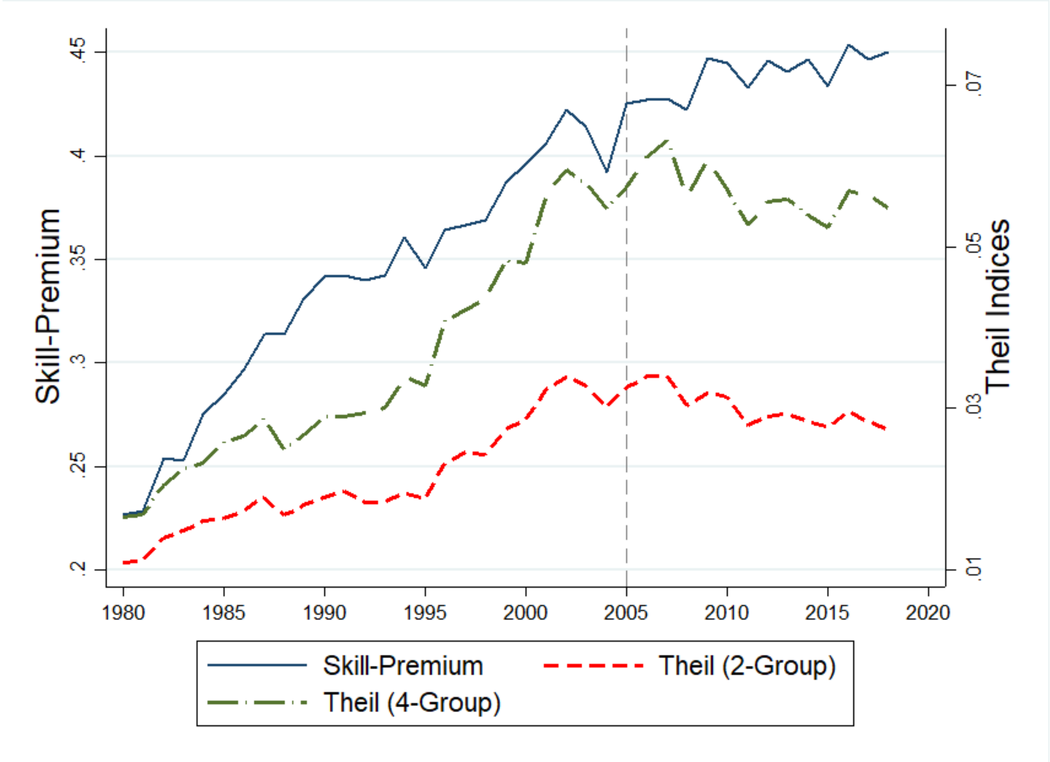


Figure 15: Annual Trends: Skill-Premium and Theil Indices for U.S. FTFY workers, 1980-2018

Notes: The yearly *skill-premium* is the coefficient of an education dummy from a wage regression estimated for individual workers from the FTFY sample, where log hourly wages have been regressed on an education dummy (some college or more), sex, two race categories (non-white, Hispanic), and a quartic in age. To estimate the 2-group Theil, the workers are split into a “no-college” experience group (education level of high-school or lower) and a “some-college” experience group (education level of at least 1 year of college). For the 4-group Theil, the workers are segregated into: “less than high-school” (those with less than Grade 12 education), “high-school” (those who have completed high-school), “some college experience” (those who have attended some college but without a degree) and “college or higher” (those with a college degree or higher).

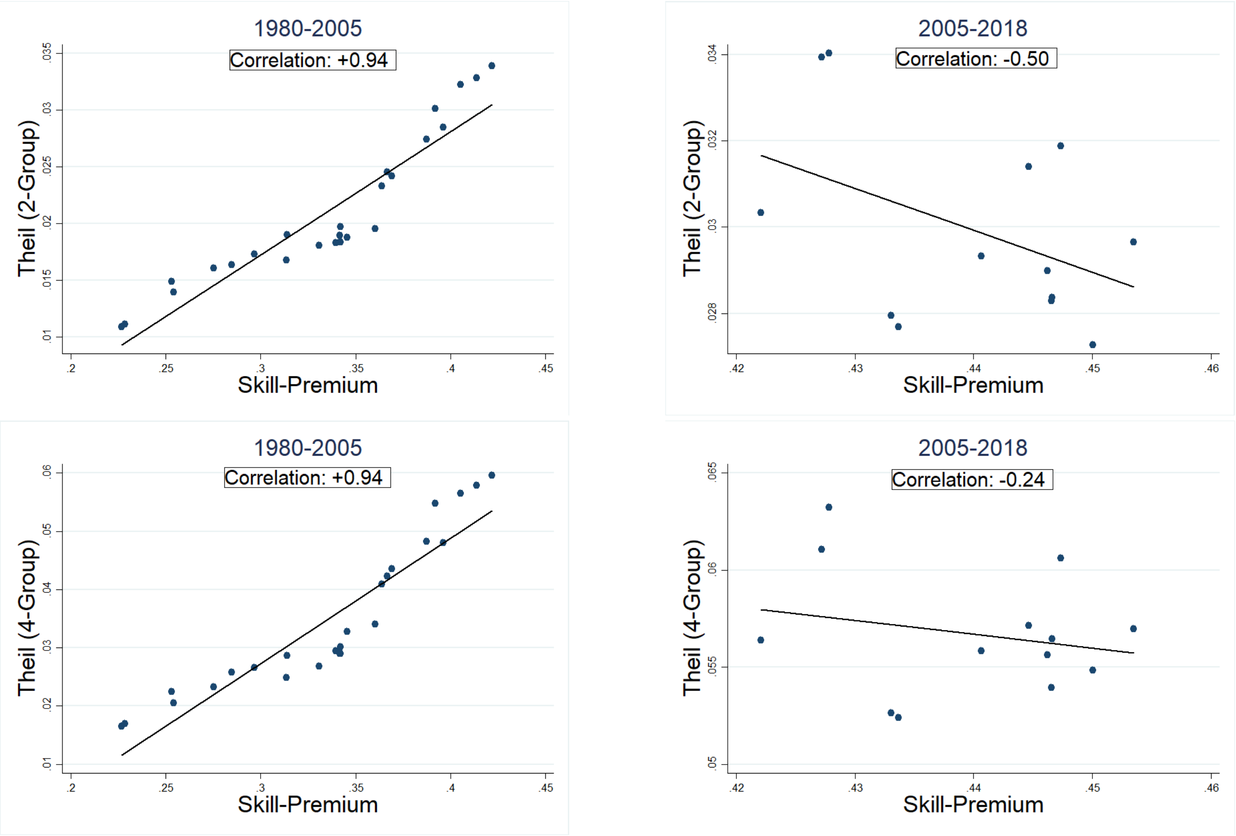


Figure 16: Correlation: Theil Indices and Skill-Premium, 1980-2005 vs. 2005-2018

Notes: The panel diagram shows how the correlations between the skill-premium and the Theil indices (2-group and 4-group) have changed over two windows: 1980 to 2005, compared to 2005 to 2018. The diagrams in the first row of the panel show the correlation between the skill-premium and the 2-group Theil over the two designated time periods, while the diagrams in the second row show the correlation between the skill-premium and the 4-group Theil.

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Appendices

Appendix A: A Skill-biased Technical Change Model with Intergenerational Investments

A1. Conditions for Interior Solution to the Utility Maximization Problem

Possible boundary solutions of the utility maximization problem can happen at $u = 0$ and $u = 1$. The corresponding value of k is given by $(\theta wu/\gamma)$ from Equation (1.8). However, note that when $u = 0$, consumption will go to zero- this violates the Inada conditions. Therefore, agents can feasibly set u close to, but never equal, to zero.

Denote the two boundary points as (u_0, k_0) and (u_1, k_1), while solutions of the utility maximization problem found in Equations (1.7) and (1.8) are u^* and k^*. The three corresponding utility levels are $U(u_0, k_0)$, $U(u_1, k_1)$ and $U(u^*, k^*)$ respectively.

First, compare the choices (u_0, k_0) to (u^*, k^*). If the agent chooses u close to zero, the value of k is also close to zero, and $U(u_0, k_0) \to 0$. Correspondingly, the utility from (u^*, k^*) is:

$$U(u^*, k^*) = ln\left(wu\left\{1 - \frac{\theta}{\gamma}\right\}\right) + \beta a\omega_{t+1}\left(1 - \frac{1}{\beta a\omega_{t+1}(\gamma - \theta)}\right) \tag{A.1}$$

Equation (A.1) will be positive given some reasonable restrictions on the model parameters- such as having sufficiently large values of β (the discount factor) and a (the skill complimentarity factor), and/or having $(\gamma - \theta) > 1$. This will lead to $U(u^*, k^*) > U(u_0, k_0)$.

For comparison with the other potential boundary solution, the utility level from (u_1, k_1) is:

$$U(u_1, k_1) = ln\left(w\left\{1 - \frac{\theta}{\gamma}\right\}\right) + \beta a\omega_{t+1}\left(1 - \left\{\frac{\gamma}{\theta w}\right\}^{\theta}\right) \tag{A.2}$$

For the agent to prefer (u^*, k^*) over (u_1, k_1) , we now need $U(u^*, k^*) - U(u_1, k_1) > 0$. Subtracting Equation (A.2) from Equation (A.1), the condition simplifies to:

$$\beta a\omega_{t+1}\left\{\frac{\gamma}{\theta w}\right\}^{\theta} > \frac{1}{(\gamma-\theta)} - ln\left[\frac{(\theta w_{j,t})^{\theta}}{a_j\beta\omega_{t+1}(\gamma-\theta)\gamma^{\theta}}\right]^{\frac{1}{\gamma-\theta}} \tag{A.3}$$

Writing $\beta a\omega_{t+1}\left\{\frac{\gamma}{\theta w}\right\}^{\theta} \equiv m$, condition (A.3) simplifies to:

$$m > \frac{1}{(\gamma-\theta)}\left[1 + ln(m) + ln(\gamma-\theta)\right] \tag{A.4}$$

Again, the previously defined restrictions can also ensure that condition (A.4) holds. Thus, the existence of an interior solution can be guaranteed to the utility maximization problem. Furthermore, as (u^*, k^*) is the only critical point of U, it follows from the extreme value theorem that this solution must be a maximum point.

Appendix B: Does Skill-biased Technical Change Improve Intergenerational Mobility of Skills? Evidence from U.S. Commuting Zones

B1. Measurement Process for Technology Measure

To calculate the technology index, I make use of a list of STEM occupations provided by the U.S. Bureau of Labour Statistics. This list is cross-matched to the occupational classification scheme in the IPUMS Census data (Ruggles et al., 2019) as provided under the *occ1990* codes, and a total of 48 unique STEM occupations are identified. I focus on the *occ1990* scheme specifically as it is a cross-walk file providing a consistent classification of occupations from 1950 onwards. In the empirical work, I make use of Census occupation and employment data from 1970, 1980, 1990 and 2000. The census samples from 1980, 1990 and 2000 include 5% of the population, with 1970 containing 1% of the population.

Once the STEM occupations have been identified, I look at the Census micro-data to calculate the technology measure as given in Equation (2.1) and the IV measure as given in Equation (2.6). All persons below the age of 18 years and over 64 years are initially dropped from the sample, along with those who work in the military. I consider persons to be employed if they indicate they are a part of the labour force, and have worked at least 1 hour in the past week. For the technology measure at the CZ level, the total employed is first calculated for each location (using an unique CZ identifier code), and then the *occ1990* codes are used to identify all those working in the STEM occupations.

To calculate the IV measure, workers are mapped to industries using the *ind1990* codes (which provides a consistent classification of industries across the Census time periods). The 1970 Census data set is first used to to calculate the total employment levels per industry per CZ in the baseline year. The STEM occupation codes are then used to determine the portion of workers of STEM profile per industry for a particular location. I then make use of the Census files from 1970, 1980, 1990 and 2000 to calculate the employment levels and STEM shares at the national industry level (a similar mapping approach of workers is followed, except that the data is aggregated at the national industry level), and these ratios are used to calculate the required growth rates.

B2. Measurement Process for Labour Market Outcomes

To carry out the wage-regression analysis, I use IPUMS Census data (Ruggles et al., 2019) for the years 1980, 1990 and 2000. I attempt to follow specifications from Acemoglu and Autor (2011)- only full-time, full-year workers, aged 18-64, are considered for the analysis, excluding those who are in the military. Full-time, full-year workers are those who have worked at least 35 hours per week and forty or more weeks in the previous year. Hourly earnings are calculated after dividing annual earnings with the amount of hours worked in a year (hours worked per week multiplied by numbers of weeks worked in the year). Nominal earnings for 1980 and 1990 are adjusted to 2000-levels using the CPI99 variable from IPUMS. Earnings of below $67 per week in 1982 dollars are dropped from the analysis. The education background of the worker is then determined from the Census data, with a worker being considered as *skilled* if he or she reported completing at least one year of college.