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Skill Formation and Inequality in Poor Countries: How Much do Ethnic Neighbourhoods Matter?

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This paper explores the potential role of social learning in the process of skill formation. It develops a model in which parents form expectations about the future returns to schooling by observing the investment behaviour of other families in their neighbourhood. This model predicts that a child's educational attainment (and hence permanent income) depends not only on parental characteristics but also on the average level of human capital in the neighbourhood where the child grew up. Empirical support for the model is found using microdata from the 1994 Ethiopian Urban Socioeconomic Survey. The data reveal that social learning has large, significant effects which are positively correlated to both a child's future income and his (adult) stock of human capital. Perhaps most important, the inclusion of neighbourhood effects raises the steady-state standard deviation of education by 64%. Neighbourhoods have a slightly smaller effect on the rate of income convergence; they raise the steady-state standard deviation of income inequality by 54%.

> Human capital accumulation is a *social* activity, involving groups of people in a way that has no counterpart in the accumulation of physical capital. (Lucas, 1988)

1. Introduction

Most types of learning involve some degree of social interaction. From the most rudimentary skills – like speaking a language – to quite

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sophisticated vocations – like buying and selling shares on the stock exchange – people tend to learn by observing those around them and then repeating their actions. Social interactions affect not only the level of skills individuals acquire but also the rate at which they accumulate new knowledge. For instance, it is often argued that children who grow up in economically advantaged neighbourhoods have higher rates of learning than those who grow up in less advantaged neighbourhoods (Coleman, 1988; Streufert, 1991; Crane, 1991; Corcoran *et al.*, 1992). High-skill neighbourhoods are believed to generate localised externalities which raise the productivity of human capital investment and thereby foster more efficient learning (Fernandez and Rogerson, 1992; Benabou, 1993a, 1993b, 1996; Durlauf, 1994, 1995, 1996). Consequently, children who grow up in different neighbourhoods are expected to experience different rates of human capital accumulation.

Recently, such issues have been the focus of much concern in the USA where increasing stratification is often criticised on the grounds of creating widening inequalities in opportunities (Wilson, 1987; Jencks and Meyer, 1990; and Kozol, 1995). By contrast, stratification and its potential effects have been largely ignored among academics and social commentators within development circles. Such neglect is somewhat surprising, given the large polarisation along ethnic lines that exists in many low-income countries. Ethnicity plays an important role in traditional societies, defining to a large extent individuals' social position, political ties and economic opportunities. Despite its influential role, few studies have investigated the extent to which ethnicity affects economic outcomes in developing countries.

To this end, this paper examines the role of social stratification in determining the pattern of skill formation within a poor economy. At the heart of the analysis lies the idea that *social learning* – knowledge acquired by observing the behaviour of other people – plays an important role in forming parents' expectations about the returns to education.[2] It is hypothesised that, in societies where information is

[2] The idea that group actions can affect individual behaviour is a central theme throughout sociology (see Brown, 1965; Fine and Kleinman, 1979; Granovetter, 1985; Coleman 1988). Most economic models, however, neglect the importance of group dynamics in determining outcomes. One exception is the growing literature

highly imperfect, parents obtain much of their information about the value of education by observing the human capital investment decisions made by their neighbours. Consequently, parents who reside in neighbourhoods where school attendance is high place a greater value on education than parents who reside in neighbourhoods where school attendance is low. Central to the analysis is the idea that parents engage in social learning because they believe that their child's probability of success is highly correlated to that of similar children in their neighbourhood. Thus, a child's educational attainment depends not only on parental characteristics but also on the average level of human capital in the neighbourhood where the child grew up.

All neighbourhood effects, however, are not transmitted via social learning. A growing body of empirical evidence suggests that neighbourhoods influence individual behaviour through a variety of mechanisms. Datcher (1982), for example, examines the impact of average neighbourhood income and racial composition in explaining the cause of earnings differentials between blacks and whites in the USA. She finds that 'at least one quarter of the gap in education and earnings of black men due to background differences can be accounted for by variations in neighbourhood quality' (p. 41). In a related study, Corcoran *et al.* (1992) demonstrate that the level of community welfare receipt is associated with other economic disadvantages. Studies by Case and Katz (1991), Crane (1991) and Evans *et al.* (1992) also provide empirical evidence of the substantial impact which neighbourhood characteristics can have on young people.[3] In a slightly different vein, Montgomery (1991) argues that 'well-connected' workers fare better in the labour market because of social ties which make it easier to find a job.[4]

on herd effects which argues that group behaviour is important because individuals obtain much of their information from the previous actions of others (see Becker 1991; Manski, 1991, 1993; Banerjee 1992; Bikhchandani *et al.*, 1992).

[3] One weakness of these studies is the possible endogeneity of peer effects. Evans *et al.* (1992) find that the impact of peer effects disappears when instruments are used and a simultaneous equation model is estimated. This study, however, does not focus on 'pure' neighbourhood effects. Instead, it focuses on the behaviour of individuals of the same ethnic group who live in the same neighbourhood.

[4] The anonymous referee for an earlier draft of this paper suggested that ethnically segregated neighbourhoods could generate several productivity effects as well. For example, ethnic neighbourhoods may engender greater mutual trust among business associates or 'may be able to sustain a critical mass for an active social life (which may have economic pay-offs)'.

The analysis carried out in this paper, however, is closest in spirit to the recent work by Borjas (1992, 1995), who highlights the potential impact of ethnic capital in the process of skill formation. As argued by Borjas (1992), 'persons who grow up in high quality ethnic environments will, on average, be exposed to social, cultural, and economic factors that increase their productivity when they grow up, and the larger or more frequent the amount of this exposure, the higher the resulting quality of worker' (p. 126). This study adopts Borjas' idea that neighbourhoods can generate positive externalities, as well as his general approach for measuring such effects. It departs significantly from Borjas' work, however, in its focus on social learning and the impact which neighbourhood ethnic effects have on skill formation within a developing country.[5]

In addition to the work by Borjas, the present study also draws heavily from the large literature on job-market signalling as developed originally by Spence (1973). In this literature employers use workers' characteristics (e.g., schooling, race, caste) as signals of worker quality because they cannot directly observe the future productivity of their applicants. Typically, such models predict that signalling leads to sub-optimal equilibria in terms of social welfare.[6] Similarly, I argue that signalling (via social learning) reduces the rate of mobility across generations.[7] Specifically, I develop and estimate a model of inter-generational mobility which takes into account the effects of ethnically segregated neighbourhoods on skill formation.

Empirical tests of the model are carried out using the 1994 Ethiopian Urban Socioeconomic Survey. Ethiopia is an interesting country in which to investigate the importance of social learning for several

[5] Only two papers to date have examined intergenerational issues within a development context (see Lillard and Willis, 1994; Thomas, 1995). Neither of these studies incorporates ethnic neighbourhood effects into the analysis.

[6] Spence (1973) argues that job market signalling can lead to an over-investment in education. Other studies find similar negative effects associated with signalling. Starrett (1976), for example, shows that poverty traps arise when disadvantaged groups believe that their probability of success is small compared with other groups. In a related study, Akerlof (1980) illustrates how some social customs (e.g., caste systems) can lead to persistent unemployment.

[7] Previous models of social learning tend to focus on its positive role in the process of technology adoption (see, e.g., Ellison and Fudenberg, 1993; Foster and Rosenzweig, 1995; Kapur, 1995). One notable exception is the study by Manski (1991), who models how teenagers form expectations about schooling based on the behaviour of the previous generation.

reasons. First, the country has strong ethnic identification. Ethiopia is home to a variety of ethnic tribes, of whom the most important in number are the Amhara, the Oromo and the Gurage. These groups are differentiated to a large extent by the regions where they live, as well as by their language and religion. Second, Ethiopia has a very poor communication system which means that its inhabitants must rely on more traditional means of information gathering. In 1992 the country had just three telephone mainlines per 1000 people and only 77 kilometres of road per million people (World Bank, 1995, Table 32). Lastly, it is possible that the country's recent history of socialism has left its people reluctant to use prices as informational signals. Given the large price distortions that existed for many years, it is likely that Ethiopians do not trust wages and other labour market signals.

The main result to emerge from the analysis is that social stratification in Ethiopia matters. Estimation of the model reveals that skill formation is significantly influenced by both parental background and the average level of neighbourhood skills. The data indicate that a child's educational attainment can be expressed as 0.27 times the education of his parent, plus 0.40 times the average education of other children in his neighbourhood, minus 0.17 times the average education of other adults in his neighbourhood, plus a constant term, plus an error term with a standard deviation of 0.07.[8] These results suggest that social learning, defined as the average education of other children in the neighbourhood, has a larger impact on skill formation than parental background.

The remainder of this paper is organised in the following manner. Section 2 explains the theoretical framework which underlies the analysis. Section 3 describes the data and the estimation techniques used for measuring the effects of social learning. Section 4 presents the main empirical results. Section 5 discusses in more detail the long-run effects of social stratification. Finally, Section 6 ends the paper with some general comments about intergenerational issues in poor economies and suggests a couple possible areas for further research.

[8] All neighbourhood averages are based on individuals who belong to the same ethnic group.

2. Theoretical Framework

The theoretical model developed in this paper draws heavily from two strands of work: first, the macroeconomic models of income distribution; and second, the microeconomic models of social learning. I start by assuming that a child's (adult) income depends primarily on the stock of human capital accumulated during childhood. Following Becker and Tomes (1979, 1986), I suppose that adults do not add to their own human capital but, instead, rely on their parents to make optimal investments for them. Put differently, the stock of skills of the next generation, $t + 1$, is determined entirely by the level of human capital investment made by the current generation, t. Parents invest in the skills of their children up to the point at which the expected return on schooling, y_{t+1}, equals the opportunity costs of funds, r.

For simplicity, there are only two periods in the model — childhood and adulthood — and two family members in each household — a parent and a child.[9] Each parent aims to maximise household welfare by choosing between his own consumption, C_t, and investments in his child's expected earnings potential, y_{t+1}. Parents finance consumption by selling their own human capital, k_t, to the market at its competitive wage, w, while they finance human capital investments in their offspring by spending quality time (i.e., time dedicated to a child's skill formation) with their children at home. Given these expenditures, the household's consumption function can be written as

$$C_t = w(1 - s_t)k_t \bar{k}_t^{\beta_3} \tag{1}$$

where s_t is the proportion of parental time devoted to a child's human capital formation.[10] Parents are assumed to be homogenous in their basic willingness to invest in their offspring but heterogenous in their expectations about the future returns to schooling.

Households are assumed to possess the following CES utility function[11]

[9] In the case of households with more than one child, it is assumed that any investments made in other children are part of the household's general consumption.

[10] Parental consumption can also be written as $C_t = y_t\,(1 - s_t)$ where $y_t = wk_t\bar{k}_t^{\beta_3}$. Like children's earnings, parental earnings are assumed to depend upon the quality of their ethnic environment, $\bar{k}_t$.

$$U = \left[\delta_1 y_{t+1}^{\rho} + \delta_2 C_t^{\rho}\right]^{1/\rho} \tag{2}$$

where y_{t+1} is the expected return to a child's human capital investment, C_t is the parent's consumption, and δ_1 and δ_2 are the values which a parent attaches to each endeavour, respectively. Parents form expectations about the returns to schooling based on their own information set. These expectations depend on the information parents receive from some combination of market signals, w, their children's human capital endowment, $\bar{k}_{t+1}$, and social learning, k_{t+1}. In other words, a child's expected returns to human capital takes the following form

$$y_{t+1} = wk_{t+1}\bar{k}_{t+1}^{\beta_3}. \tag{3}$$

Implicit in this functional form is the idea that parents' expectations are rational because children who grow up in economically advantaged neighbourhoods benefit from the positive externalities that are generated by their peers. Holding all else constant, a child's expected earnings are higher the greater the value of $\bar{k}_{t+1}$, which is assumed to be proportional to the average level of education of other children in the neighbourhood from the same ethnic group.

The idea that expectations vary across individuals has been confirmed in a couple of recent empirical studies. Betts (1996), for example, examines the responses of undergraduates in the USA who were asked to report how much workers with different education earned. His findings reveal that students' wage expectations vary substantially with their own level of education and personal background. According to Betts (1996: 37), 'students whose parents' income was less than $50,000 tended to make significantly lower estimates of earnings of college graduates than did students in the excluded group, which was students whose parents' income exceeded $75,000'. In a similar study, Dominitz and Manski (1996) find substantial within-group variation among students classed by gender and level of schooling. Like the above studies, this paper posits that

[11] I chose a constant elasticity of substitution (CES) utility function because the model assumes that investments in child quality are constant within sub-cultural groups but vary across the total population. In a related paper, Borjas (1992) also adopts a CES framework in his study which isolates the effects of ethnic social capital. Like Borjas, I drop the CES functional form when estimating the model by assuming that $\rho = 0$ and adopting a Cobb–Douglas functional form.

expectations vary across individuals who are exposed to different informational signals.

Up to this point I have not mentioned how I will incorporate the effects of neighbourhoods into the analysis. Following the seminal work of Ben-Porath (1967), I assume that the process of skill formation can be modelled using an educational production function. The process of skill formation takes the following form

$$k_{t+1} = \beta_0 (s_t k_t)^{\beta_1} \bar{k}_t^{\beta_2} \tag{4}$$

where k_{t+1} is a child's human capital, $s_t k_t$ is the amount a parent invests in child quality and k_t is the average level of skills of the ethnic group in the neighbourhood. This expression suggests that a child's human capital is determined both by intra-household decisions (i.e., the value of investment made by his parents) and neighbourhood ethnic effects (i.e., the amount of ethnic capital accumulated through social contact in the neighbourhood).

Implicit in equation (4) is the assumption that parental time and ethnic capital are complements in the process of human capital formation. Moreover, the specification suggests that children with greater endowments of ethnic capital in their neighbourhood are more efficient, *ceteris paribus*, in converting educational investment into units of human capital. This idea that external factors can raise the productivity of human capital investment is by no means new. In addition to the recent empirical work on neighbourhood effects, a number of older studies also have revealed the statistical importance of peer effects using educational production functions (see, e.g., Summers and Wolfe, 1977; Henderson *et al.*, 1978; Arnott and Rowse, 1987; Dynarski and Zampelli, 1989). Moreover, several theoretical papers have modelled both the macroeconomic effects (Lucas, 1988; Benabou, 1993a) and the microeconomic effects (Acemoglu, 1996) of increasing returns in human capital accumulation.

Parents choose how much to invest in the future earnings of a child by maximising equation (2) with respect to s_t. Given their household budget constraint, equation (1), and the constraint placed on human capital formation, equation (4), a child's earnings potential is determined by

$$\ln y_{ij}(t+1) = \alpha + \gamma_1 \ln y_{ij} + \gamma_2 \ln \bar{y}_j(t) + \gamma_3 \ln \bar{y}_j(t+1) + \varepsilon \tag{5}$$

where α is a constant term, $y_{ij}(t+1)$ is the (adult) earnings of child i who belongs to ethnic group j, $y_{ij}(t)$ is parental earnings, $\bar{y}_j(t)$ is ethnic

capital, $\bar{y}_j(t+1)$ is ethnic social learning, and ε is a stochastic error term which follows $\varepsilon \sim N(0, \sigma_2)$. From equation (5) it can be seen that neighbourhood ethnic effects raise a parent's propensity to invest in human capital (via social learning) and also increase the productivity of such investments (via ethnic capital).

If we assume that there is no sorting so that the (adult) earnings of a child, y_{t+1}, and the earnings of parents, y_t, are identical across neighbourhoods (i.e., that $\bar{y}_{t+1} = y_{t+1}$ and $\bar{y}_t = y_t$), then the (average) elasticity of child earnings with respect to parental earnings can be derived as

$$\eta = \frac{\gamma_1 + \gamma_2}{(1-\gamma_3)} \tag{6}$$

where η is interpreted as the (average) rate at which earnings are converging toward or diverging away from the mean from one generation to the next. The rate of mobility across generations is slower the larger the value of h whose value is determined by both parental and neighbourhood characteristics.

It is easy to see that the model outlined in equatin (5) is just an extension of previous models of intergenerational mobility as developed by Becker and Tomes (1979, 1986) and Borjas (1992, 1995). A typical specification of the Becker and Tomes model is

$$\ln y_{t+1} = \alpha + \gamma_1 \ln y_t + \varepsilon_{t+1}. \tag{7}$$

In this model the transmission coefficient is γ_1, which is the same as the parental coefficient. Therefore, the degree of inequality across generations is determined largely by intra-household factors (e.g., parental income). As stated by Becker and Tomes (1986), the size of γ_1 also measures whether children of richer parents tend to be less rich than their parents and whether children of poorer parents tend to be better off than their parents. This example implies that even in rigid and caste-dominated societies, many of the elite and underprivileged families would change places over generations unless inequality continues to grow over time ($\gamma_1 \geq 1$)(p. 52).[12]

Borjas (1992) extends the Becker and Tomes framework by including

[12] This is my notation, not that of Becker and Tomes (1986).

the effects of ethnic capital into the model of intergenerational mobility. He states, 'the skills of the next generation depend not only on parental inputs, but also on the average quality of the ethnic environment, or 'ethnic capital'' (p. 124). A general specification of the Borjas (1992) model is

$$\ln y_{t+1} = \alpha + \gamma_1 \ln y_t + \gamma_2 \ln \bar{y}_t + \varepsilon_{t+1} \tag{8}$$

where γ_1 is the parental coefficient and γ_2 is the coefficient on 'ethnic capital'. Because Borjas assumes that inequality is influenced by both intra-household and external factors, the transmission coefficient also includes these effects; that is, $\eta = \gamma_1 + \gamma_2$. In a later paper, Borjas (1995) defines 'ethnic capital' as the mean skills of adults within a neighbourhood who have the same ethnicity. Borjas focuses solely on adult ethnic capital (i.e., the skills of individuals from the parent's generation) because he hypothesises that many localised externalities arise due to adult influences (e.g., role model effects, cultural attitudes).

In this paper, the effects of both ethnic capital and ethnic social learning are taken into account. Intergenerational mobility is believed to be influenced not only by the parent's generation but also by the child's generation. As discussed above, this is because the school enrolment of a child's peers is assumed to affect the rate at which a child accumulates skills. A generalised form of the model developed in this paper is

$$\ln y_{t+1} = \alpha + \gamma_1 \ln y_t + \gamma_2 \ln \bar{y}_t + \gamma_3 \ln \bar{y}_{t+1} + \varepsilon_{t+1} \tag{9}$$

where γ_1 is the parental coefficient, γ_2 is ethnic capital, γ_3 is the coefficient on social learning, and $\eta = \gamma_1 + \gamma_2/(1 - \gamma_3)$. From the above equation it is obvious that the exclusion of social learning will bias the transmission coefficient downwards provided that $(\gamma_1 + \gamma_2)$ are positive. The larger the value of γ_3, the larger the bias in η due to the omission of social learning effects.

3. Data and Empirical Estimation

This study employs an usually rich data set to investigate the role of social learning and ethnic capital in determining the rate of income and educational mobility across generations. Data are drawn from the 1994 Ethiopian Urban Socioeconomic Survey (EUSS), an urban survey of 1500 households. This survey was jointly administered by the

University of Addis Ababa, Ethiopia and the University of Göteborg, Sweden. Like most household surveys, it contains the usual information on family demographics (e.g., size, relationship to head, age, sex, marital status), but it also contains some unusual information which makes it ideal for testing the importance of neighbourhood ethnic effects on intergenerational mobility.

The most important feature of the data for the purposes of this study is the information they contain on a large number of families where adults from two generations are living together. Few data sets contain such information, which explains why so little empirical research has examined intergenerational issues within both rich and poor countries. Although the EUSS was not designed specifically to address questions of intergenerational mobility, the prevalence of multi-generational (adult) households within urban Ethiopia means that the data can be used for such purposes. Households containing large, extended families are common for a couple of reasons: first, family ties are strong, and second, many adults in urban areas are unable to move out of their parent's home because of the severe housing shortages due to rapid urbanisation.

Like other poor countries, the rapid urbanisation in Ethiopia has occurred mainly as a result of rural-urban migration spurred by the large wage differentials existing between rural and urban areas. However, the country's precarious political situation has also exacerbated the problem. After the new government took power in 1991, the country experienced a radical shift in the organisation of regional power structures which led to much uncertainty and, in some areas, forced migration of some ethnic groups. This uncertainty has led to a rapid rise in the population of cities and, consequently, severe housing shortages.

As explained in Section 2, the econometric model used to capture the effects of ethnic social learning and ethnic capital is an extension of the model of intergenerational mobility developed originally by Becker and Tomes (1979, 1986). In equation (9), the speed at which incomes converge toward the mean is negatively associated with the size of the parameter γ_1. Stated differently, the rate of income mobility — both upwards and downwards — is faster, the closer γ_1 is to zero.

Estimates of γ_1, however, are likely to be biased downward if there are significant (positive) neighbourhood externalities which get transmitted across generations. The size of such biases are unknown until controls for neighbourhood ethnic effects are included in the

intergenerational model and the coefficients on γ_1 are compared. One method of capturing neighbourhood ethnic effects is by the following equation

$$(10) \qquad y_{ij}(t+1) = \gamma_1 y_{ij}(t) + \sum_{k+1}^{200} \lambda_j(t+1) D_{ij} + \varepsilon_{ij}(t+1)$$

where is D_{ij} a dummy variable indicating whether child i lives in neighbourhood k and λ_j is a vector of neighbourhood ethnic fixed effects.

As outlined in the theoretical discussion, the model assumes that neighbourhood ethnic fixed effects include influences from social factors, such as social learning and ethnic capital. Therefore, the vector of neighbourhood ethnic fixed effects, j, can be written as

$$(11) \qquad \lambda_j(t+1) = \gamma_0 + \gamma_2 \bar{y}_j(t) + \gamma_3 \bar{y}_j(t+1) + v_j(t+1)$$

where $\bar{y}_j(t)$ is the average (log) earnings of neighbours in the parent's generation who have the same ethnicity, and $\bar{y}_j(t+1)$ is the average (log) earnings of the child's peer group (i.e., children in the neighbourhood with the same ethnicity).[13] In this paper, the coefficient on $\bar{y}_j(t+1)$ is interpreted as a measure of the extent to which social learning affects the future economic success of a child. By defining social learning in terms of the average income of other children in the neighbourhood, I am assuming that parents observe the rates of school enrolment of children who are slightly older than their own, and then make human capital investment decisions which are based, at least in part, on the schooling decisions of other families. Of course, there are several other ways in which $\bar{y}_j(t+1)$ can be interpreted. For instance, $\bar{y}_j(t+1)$ may capture the effects of peer influences or social contacts in the labour market.

To obtain the rate of mobility (net of neighbourhood effects), I

[13] It should be pointed out that some neighbourhoods did not have data on another person from the same ethnic group. For those neighbourhoods, $y_i(t+1)$ and $y_j(t)$ were calculated as the average earnings of other individuals in the neighbourhood who belonged to the appropriate generations. Only 15% of all neighbourhoods in the total sample, however, were composed of only one ethnic group.

substitute equation (11) back into equation (10) to get the following equation

$$(12) \qquad y_{ij}(t+1) = \gamma_0 + \gamma_1 y_{ij}(t) + \gamma_3 \bar{y}_j(t+1) + \varepsilon_{ij}(t+1)$$

where $y_j(t+1) \sim N(0, \sigma_2)$. It is this specification which is regressed to obtain estimates of η.[14] Equation (12) is estimated on a sample of 309 male and female (adult) children who reside with their parents. The definitions of the variables used in the regression are fairly straightforward. A child's education (or income), $y_{ij}(t+1)$, is defined simply as his years of schooling (or weekly earnings). In addition, parental education, $y_{ij}(t)$, is defined in terms of years of schooling. Parental income, however, is defined as the average weekly wage for all adults in the parent's generation with the same education. Although it would have been preferable to include the parent's own wage directly into the regression, the large number of missing observations meant that such a regression would have few degrees of freedom. Finally, social learning and ethnic capital are defined as the average education (or income) of the child's peer group and his parent's peer group, respectively. I define a peer group as all others in the neighbourhood who have the same ethnicity and belong to the same generation.[15]

To calculate generational averages, I divided the sample into two groups based on age: generation (t) are those aged 40+, and generation ($t+1$) are those aged 18 to 40. These categories were then used to construct the variables interpreted as social learning and ethnic capital. I define the bottom age limit for generation ($t+1$) as 18 because $y(t+1)$ is assumed to represent permanent income. Obviously, the wage of an 18-year-old is unlikely to match his permanent income, given the usual pattern of life-cycle earnings. To control for life-cycle wage variations, I include the child's age and its square in the estimated regressions. Similarly, I include a dummy variable

[14] There is a possible endogeneity problem with the social learning variable as specified in (12). The endogeneity problem arises because the earnings of person i in generation $t+1$ depend on the earnings of person $j \neq i$ in the same generation. For the purposes of this paper, I assume that the social learning effects are exogenous.

[15] Because of the small sample size within some neighbourhoods, the variables $\bar{y}_t$ and $\bar{y}_{t+1}$ exclude the parent's and child's own characteristics, respectively. For example, the average earnings of a child's peer group, $\bar{y}_{t+1}$, do not include the child's own earnings.

Table 1: *Descriptive Statistics of Generation* (t+1)

Variable	Mean	Standard Deviation
(Log) wage, y_{t+1}	3.98	0.82
Schooling, s_{t+1}	11.2	3.59
(Log) parent's wage, y_t	4.21	0.39
Parent's schooling, s_t	3.84	4.66
(Log) ethnic capital based on income, $\bar{y}_t$	4.26	0.8
Ethnic capital based on schooling, $\bar{s}_t$	1.11	0.81
(Log) social learning based on income, $\bar{y}_{t+1}$	4.05	0.62
Social learning based on schooling, $\bar{s}_{t+1}$	2.2	0.29
Male	0.58	0.5
Age	26.6	5.09
Amhara	0.6	0.49
Tigrayan	0.07	0.26
Oromo	0.17	0.38
Gurage	0.13	0.34
Other	0.03	0.17
Capital city	0.8	0.4
Migrant	0.05	0.23

Notes: ethnic capital is defined as the average earnings (or years of education) of generation (t). Social learning is defined as the average earnings or years of education) of generation (t + 1). Migrant status indicates whether the household moved to the city within the past 10 years.

indicating whether the child is male in order to control for gender-based wage differentials, as well as a set of dummy variables indicating the household's city location and migrant status. These latter variables are included to control for regional wage variation and unobservable household characteristics which are correlated with migration.

Since little is known about young urban workers in Ethiopia, Table 1 provides some descriptive statistics of the sample upon which the analysis is based. Perhaps the most striking characteristic of the children's generation is the high level of average education. Generation t+1 has an average education of 11 years which is about three times that of the older generation. The large jump in average

Table 2: *Levels and Growth in Education Across Ethnic Groups*

Variable	All Adults	Amhara	Tigrayan	Oromo	Gurage	Others
Mean years of education	7.76 (4.87)	8.01 (4.84)	7.62 (5.09)	7.49 (4.76)	7.35 (4.76)	6.85 (5.02)
Growth per year (mean)	0.0187 (0.0007)	0.0184 (0.0009)	0.0182 (0.0023)	0.0182 (0.0017)	0.0225 (0.0021)	0.0184 (0.0028)
Sample size	4159	2238	377	708	529	307

Notes: standard deviations are reported under the values for mean years of education. Growth rates per year are estimated by regressing (log) years of education on birth year. The standard errors are reported under the growth rates.

education between generations suggests that programmes of educational expansion within urban areas have been very successful during the past few decades. Historical rates of school enrolment also support this view. According to the World Bank (1989, Table 32), the percentage of school-age children enrolled in education between 1965 and 1986 rose from 11 to 36% (World Bank, 1989, Table 32). However, evidence from the EUSS reveals that the estimated (mean) growth rate of education per year[16] has remained constant across generations. The growth rate of education for all adults is estimated at approximately 0.019, indicating that (average) education increases by about two years each decade.

As illustrated by Table 2, the rates of growth have been fairly equal across ethnic groups. Ethiopia has five major ethnic groups (i.e., Amhara, Tigrayan, Oromo, Gurage and Somali), as well as numerous smaller groups (e.g., Harari, Afar, Kembata, Hadiya, Wolaita, Dorze, Sidama, Keffa, Gamo, Yem, Seltie and Kebena). Although ethnic ties are often weaker in urban areas than they are in rural areas, ethnicity still plays a prominent role in urban culture and politics. Certain ethnic groups tend to concentrate in certain cities and some kebeles have a

[16] This estimate is calculated by regressing (log) years of education on year of birth. The coefficient on birth year for generation (t) and generation ($t + 1$) is 0.0177 and 0.0171, respectively.

higher concentration of particular ethnic groups than others. However, it is the heterogeneity of urban neighbourhoods which enables me to measure the effects of social learning by defining peer groups in terms of ethnicity.

4. Empirical Results

Table 3 reports the estimated rates of income convergence across generations in Ethiopia. The first four columns reveal a strong relationship between the incomes of Ethiopian children and that of their parents. Notice that the parental coefficient varies from 0.30 to 0.36, depending upon the number of controls included in the model. Surprisingly, the estimated parental coefficient in Ethiopia is very close to that estimated by Solon (1992) and Zimmerman (1992) for the USA; they estimate a parental coefficient of 0.4. Since one expects the level of inequality to be much lower in the USA, it is somewhat puzzling that the coefficients on parental income are so similar in magnitude. One would expect the rate of income convergence within Ethiopia to be much slower than the rate of income convergence in the USA.

Less surprising results are revealed, however, once controls are included for the effects of social learning and ethnic capital. The inclusion of these variables substantially increases the estimated rate of mean convergence from 0.30 (column 4) to 0.36 (column 8) which is a rise of about 20%. This suggests that models which exclude neighbourhood characteristics – like social learning and ethnic capital – are likely to overestimate the rate of income mobility across generations.[17] Indeed, the estimated transmission coefficient is slightly higher in Ethiopia than it is in the USA when neighbourhood effects are taken into account. Borjas (1995) estimates the mean rate of income convergence for the USA at 0.27; the estimated rate for Ethiopia is 0.30. Although the Borjas model is slightly different from the model estimated in this paper, it does include many of the same control variables (e.g., ethnic capital, neighbourhood fixed effects and ethnic fixed effects) which means it should be roughly comparable.

Overall, the results from Table 3 provide strong empirical support

[17] Remember an increase in the mean rate of convergence translates into a slower rate of intergenerational mobility.

Table 3: *Estimates of Income Convergence Across Generations*

	Model I				Model II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parental income, y_t	0.3560*	0.3066*	0.3264*	0.2926*	0.2960*	0.2549*	0.2785*	0.2462
	(0.1231)	(0.1218)	(0.1214)	(0.1237)	(0.1124)	(0.1244)	(0.1211)	(0.1281)
Neighbourhood ethnic capital, $\bar{y}_t$	x	x	x	x	-0.0001	-0.0113	0.0084	0.0060
	(0.0745)	(0.0621)	(0.0772)	(0.0638)				
Neighbourhood social learning, $\bar{y}_{t+1}$	x	x	x	x	0.3142*	0.3165*	0.2962*	0.3033*
	(0.0877)	(0.0749)	(0.0912)	(0.0794)				
Intergenerational transmission coefficient, η	0.356	0.3066	0.3264	0.2926	0.4315	0.3564	0.4076	0.362
Includes neighbourhood fixed effects	no	yes	no	yes	no	yes	no	yes
Includes ethnic fixed effects	no	no	yes	yes	no	no	yes	yes
Includes neighbourhood characteristics	no	no	no	yes	no	no	no	yes
Adjusted R^2	0.1328	0.1358	0.1496	0.1509	0.189	0.1883	0.1948	0.206

Notes: Huber standard errors reported in parentheses, except in regressions (2), (4), (6) and (8) which use a fixed-effects estimator. All regressions control for gender, age and its square, city location, and household migrant status. Statistical significance at the 1% and 5% levels are indicated by * and **, respectively.

for the argument that neighbourhood ethnic effects matter. Notice in column (5) that the coefficient on $\bar{y}_{t+1}$ is larger than the coefficient on y_t, indicating that social learning has a greater impact on children's income than parental background. It is possible, of course, that $\bar{y}_{t+1}$ is not measuring social learning at all but, instead, picking up unobserved neighbourhood characteristics. To test the robustness of the coefficient on $\bar{y}_{t+1}$, several specifications were estimated which added to the model a number of controls highly correlated with neighbourhood quality. The model was re-estimated with neighbourhood fixed effects (columns 6 and 8), ethnic fixed effects (column 7) and an additional vector of neighbourhood characteristics (column 8). Variables included in this vector include neighbourhood unemployment rates, adult illiteracy rates, average household expenditures on schooling and the proportion of workers who found employment through a social contact. Despite these controls, the coefficient on $\bar{y}_{t+1}$ remained significant at the 1% level.[18] By contrast, the coefficient on ethnic capital is never significant.

In Table 4 the model is re-estimated with child's schooling added as a regressor. This model estimates the rate of income convergence, net of the mobility effects which occur as a result of education. As expected, the size of the parental coefficients falls after educational effects have been 'netted' out. This is because higher parental income enables children to acquire more education which, in turn, makes them more productive and earn higher wages. Indeed, parental income has no explanatory power in the model, once educational effects are netted out. On the other hand, social learning remains significant, which suggests that this variable may be picking up some additional effects, like social networks or peer influences.[19] The coefficient on social learning, however, does fall by over a third when a child's education

[18] In the Borjas (1995) study, the inclusion of a similar vector of neighbourhood characteristics reduces the transmission coefficient from 0.36 to 0.27 in the education equations. He states 'a small vector of variables that are common to all persons in the neighbourhood, regardless of ethnic background, can explain over half the drop in the ethnic-capital coefficient' (p. 380). The inclusion of neighbourhood characteristics in the Ethiopian data, however, produces a drop in the transmission coefficient of only 19%.

[19] If the only effect of social learning were that it raised a child's level of schooling, one would expect it to be insignificant in Table 4. The fact that it is not suggests that social learning generates other effects as well as raising a child's level of schooling.

Table 4: *Estimates of Income Convergence across Generations, Net of Mobility Effects due to Child's Education*

	Model I				Model II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parental income, y_t	0.1496	0.1257	0.1202	0.1057	0.1145	0.1003	0.0922	0.0936
	(0.1056)	(0.1193)	(0.0991)	(0.1226)	(0.1018)	(0.1224)	(0.0983)	(0.1257)
Child's education, s_{t-1}	0.0768*	0.0771*	0.0787*	0.0777*	0.0693*	0.0694*	0.0716*	0.0706*
	(0.0175)	(0.0131)	(0.0179)	(0.0133)	(0.0181)	(0.0130)	(0.0185)	(0.0133)
Neighbourhood ethnic capital, $\bar{y}_t$	x	x	x	x	0.0136	–0.0052	0.0259	0.0126
	(0.0736)	(0.0594)	(0.0754)	(0.0609)				
Neighbourhood social learning, $\bar{y}_{t+1}$	x	x	x	x	0.2478*	0.2517*	0.2195*	0.2341*
	(0.0909)	(0.0726)	(0.0886)	(0.0769)				
Intergenerational transmission coefficient, η	0.1496	0.1257	0.1202	0.1057	0.1703	0.1271	0.1513	0. 1387
Includes neighbourhood fixed effects	no	yes	no	yes	no	yes	no	yes
Includes ethnic fixed effects	no	no	yes	yes	no	no	yes	yes
Includes neighbourhood characteristics	no	no	no	yes	no	no	no	yes
Adjusted R^2	0.2297	0.2295	0.2451	0.2552	0.2625	0.262	0.2709	0.281

Notes: Huber standard errors reported in parentheses, except in regressions (2), (4), (6) and (8) which use a fixed-effects estimator. All regressions control for gender, age and its square, city location, and household migrant status. Statistical significance at the 1% and 5% levels are indicated by * and **, respectively.

Table 5: *Estimates of Convergence in Educational Attainment Across Generations*

	Model I				Model II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parental education, s_t	0.2227*	0.1950*	0.2206*	0.1869*	0.2725*	0.2461*	0.2809*	0.2531*
	(0.0437)	(0.0431)	(0.0479)	(0.0446)	(0.0602)	(0.0521)	(0.0623)	(0.0527)
Neighbourhood ethnic capital, $\bar{s}_t$	x	x	x	x	–0.1827**	–0.1668**	–0.2053**	–0.1926**
	(0.0863)	(0.0839)	(0.0855)	(0.0860)				
Neighbourhood social learning, $\bar{s}_{t+1}$	x	x	x	x	0.4049*	0.3750*	0.4113*	0.3544*
	(0.0955)	(0.0923)	(0.0935)	(0.1017)				
Intergenerational transmission coefficient, η	0.2227	0.195	0.2206	0.1869	0.1509	0.1269	0.1284	0.0937
Includes neighbourhood fixed effects	no	yes	no	yes	no	yes	no	yes
Includes ethnic fixed effects	no	no	yes	yes	no	no	yes	yes
Includes neighbourhood characteristics	no	no	no	yes	no	no	no	yes
Adjusted R^2	0.1709	0.166	0.1907	0.1871	0.2319	0.2062	0.2539	0.2547

Notes: Huber standard errors reported in parentheses, except in regressions (2), (4), (6) and (8) which use a fixed-effects estimator. All regressions control for gender, age and its square, city location, and household migrant status. Statistical significance at the 1% and 5% levels are indicated by * and **, respectively.

is added as a regressor; the coefficient falls from 0.36 in column (8) of Table 3 to 0.23 in column (8) in Table 4. This suggests that the impact of social learning on income mobility does operate, as expected, via increased education.

The effects of social learning are investigated further in Table 5, which reports the results from estimating the educational mobility equation. Columns (1)–(4) reveal that parental education plays a large role in determining how much education a child receives. The parental coefficient varies from 0.19 to 0.23 which, once again, is similar to the estimates of the parental coefficient for the USA. Borjas (1995) estimates the parental coefficient in the USA to range between 0.17 and 0.24.[20] Unlike the income mobility model, however, the inclusion of social learning and ethnic capital do not increase the value of the transmission coefficient. On the contrary, they lower the rate of intergenerational transmission from 0.19 (column 4) to 0.09 (column 8). This suggests that neighbourhood characteristics have positive effects which increase the rate of educational mobility. Notice, for example, that the inclusion of neighbourhood characteristics increases slightly the value of the parental coefficient. By comparing the results reported in columns (1) and (5), we see that the parental coefficient rises from 0.22 to 0.27. This suggests that neighbourhood effects have both a direct and an indirect effect on skill formation. They increase a child's schooling directly through the positive effects of social learning and indirectly by strengthening the influence of parents' education.

Quite surprisingly, ethnic capital has a negative effect on skill formation. This may be interpreted as evidence that parents who live in neighbourhoods with low skills realise that the only way for their children to escape poverty is through increased education. Although this explanation is desirable for welfare reasons, it is unlikely given the fact that a move from no educational segregation to complete education segregation increases the steady-state standard deviation of education by 64%. This latter result suggests that segregation increases the rate of educational inequality across many generations rather than reducing it.

[20] The Borjas results are based on data from the National Longitudinal Survey of Youth. Considerably larger coefficients are found when the estimation is based on the 1970 Census. Estimates of the parental coefficient from the Census data range from 0.17 to 0.36.

Table 6: *Estimates of Convergence in Educational Attainment Across Generations, Net of Mobility Effects due to Parental Income*

	Model I				Model II			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parental education, s_t	0.2015*	0.1722**	0.2049*	0.1713**	0.2335*	0.2092*	0.2416*	0.2133*
	(0.0767)	(0.0775)	(0.0670)	(0.0814)	(0.0639)	(0.0781)	(0.0712)	(0.0818)
Parental income, y_t	0.0028	0.0030	0.0020	0.0020	0.0057	0.0054	0.0056	0.0056
	(0.0085)	(0.0086)	(0.0046)	(0.0089)	(0.0047)	(0.0084)	(0.0050)	(0.0871)
Neighbourhood ethnic capital, $\bar{s}_t$	x	x	x	x	-0.1925**	-0.1760**	-0.2159**	-0.2011**
	(0.0892)	(0.0852)	(0.0892)	(0.0878)				
Neighbourhood social learning, $\bar{s}_{t+1}$	x	x	x	x	0.4051*	0.3751*	0.4111*	0.3559*
	(0.0949)	(0.0924)	(0.0930)	(0.1018)				
Intergenerational transmission coefficient, h	0.2015	0.1722	0.2049	0.1713	0.0689	0.0531	0.0436	0.0189
Includes neighbourhood fixed effects	no	yes	no	yes	no	yes	no	yes
Includes ethnic fixed effects	no	no	yes	yes	no	no	yes	yes
Includes neighbourhood characteristics	no	no	no	yes	no	no	no	yes
Adjusted R^2	0.1708	0.1662	t0.1909	0.1973	0.2331	0.2309	0.255	0.2558

Notes: Huber standard errors reported in parentheses, except in regressions (2), (4), (6) and (8) which use a fixed-effects estimator. All regressions control for gender, age and its square, city location, and household migrant status. Statistical significance at the 1% and 5% levels are indicated by * and **, respectively.

The importance of income constraints in restricting human capital investment is examined in Table 6. In column (1), the rate of educational mobility falls only slightly when total household income is added to the equation as a regressor. This result suggests that income constraints are not a major factor in explaining the variation in educational attainment across generations. However, the estimated value of the transmission coefficient falls substantially when neighbourhood fixed effects are included in the regression. Notice that η falls to 0.05 in column (6) after the introduction of both neighbourhood fixed effects and household income. This result suggests that neighbourhood characteristics influence the rate of educational mobility more than parental income.

5. Do Neighbourhood Effects Matter in the Long Run?

Although the results reported in Section 4 provide a great deal of evidence on the extent to which neighbourhoods influence the transmission of skills and earnings from one generation to the next, they provide no insight into the long-run effects of social stratification. In this section, I demonstrate that neighbourhood characteristics can have persistent effects which last for many generations. To see the intuition, consider the following relationship

$$s(t+1) = \alpha + \gamma_1 s(t) + \varepsilon(t+1). \tag{13}$$

This equation represents a typical AR(1) process in which the parental coefficient, γ_1, is interpreted as an autocorrelation coefficient. As discussed above, models of intergenerational mobility like equation (13) predict that the economic prospects of the future generation are affected by the economic outcomes of the past generation. If we assume that a child's future economic prospects are only affected by intra-household factors (i.e., all children grow up in the same social environment), then the long-run standard deviation of $s(t + 1)$ can be expressed as $\sigma_{y(t+1)} = \sigma_\varepsilon/\sqrt{(1 - \gamma_1)}$. Since we know that $\gamma_1 = 0.27$ and $\sigma_\varepsilon = 0.07$ from the results of Table 5, it is it easy to see that the steady-state standard deviation of education is 0.07.[21] This result suggests that if there were 'no sorting' in Ethiopia, the long-run level of educational

[21] See Johnson (1991: 289–90) for the intuition behind how to calculate the steady-state standard deviation in the case of one lagged explanatory variable.

inequality would be 0.07, which is much less than one year. Similarly, the steady-state standard-deviation of the log of income inequality would be 0.02, which is also very small.

Now, consider the opposite case of 'perfect sorting'. If there were perfect educational segregation, then all residents within a neighbourhood would have exactly the same level of schooling (i.e., $\bar{s}(t+1) = s(t+1)$, and $\bar{s}_t = s_t$). The intergenerational model in the case of perfect sorting is written as

$$s(t+1) = \alpha + \gamma_1 s(t) + \gamma_2 s(t) + \gamma_3 s(t+1) + \varepsilon(t+1). \tag{14}$$

With a little algebraic manipulation equation (14) can be rewritten as

$$s(t+1) = \frac{\alpha}{1-\gamma_1} + \frac{\gamma_1+\gamma_2}{1-\gamma_3} s(t) + \frac{\varepsilon(t+1)}{1-\gamma_3}. \tag{15}$$

By comparing equation (15) with equation (13) we can derive the steady-state standard deviation of education for the case of perfect segregation as

$$\sigma_{s_{t+1}} = \frac{\frac{\sigma_{\varepsilon(t+1)}}{1-\gamma_3}}{\sqrt{1-\left(\frac{\gamma_1+\gamma_2}{1-\gamma_3}\right)^2}}. \tag{16}$$

From the results reported in Table 3, we know that $\sigma_{\varepsilon(t+1)} = 0.07$, $\gamma_1 = 0.27$, $\gamma_2 = -0.18$, and $\gamma_3 = 0.40$.[22] Therefore, the steady-state standard deviation of education in the case of perfect sorting is 0.12. Although this standard deviation is quite small, it is 64% larger than the standard deviation in the no sorting case. Similarly, the steady-state standard deviation of the log of income in the case of perfect segregation is 54% greater than it would be in a heterogeneous society. Thus, the empirical evidence suggests that social stratification plays a central role in explaining the persistent inequality within Ethiopia.

[22] See Kremer (1997) for a similar derivation.

6. Conclusion

This paper develops and estimates a model of intergenerational mobility in which skill formation is influenced by neighbourhood effects. In this model, parents form expectations about the future returns to education by observing the investment behaviour of other families in their neighbourhood. It is posited that a child's educational attainment (and hence permanent income) depends not only on parental characteristics but also on the average level of human capital in the neighbourhood where he grew up. Empirical support of the model is found using microdata from the 1994 Ethiopian Urban Socioeconomic Survey. The analysis provides strong evidence that neighbourhood characteristics affect the rate of intergenerational mobility. Indeed, it is revealed that social learning has a larger impact on a child's educational attainment than parental background.

Moreover, the analysis demonstrates that a failure to control for neighbourhood effects when estimating intergenerational models can lead to biased coefficients. Without neighbourhood effects, the Ethiopian data predict a rate of income convergence that is faster than the rate estimated for the USA. Once neighbourhood effects are taken into account, however, the predicted rate of income convergence falls below that of the USA. Thus, there is evidence that neighbourhood effects substantially reduce the rate of income mobility by widening the disparity in incomes across neighbourhoods. On the other hand, the evidence also suggests that neighbourhood effects increase the rate of educational mobility. This result arises because ethnic capital has such a large negative effect on skill formation.

Perhaps most importantly, the analysis reveals that neighbourhood characteristics affect mobility not just in the short run but also in the long run. By comparing the hypothetical cases of 'no sorting' and 'perfect sorting', it is revealed that neighbourhoods increase the steady-state standard deviation of education by 64%. Neighbourhood effects have a slightly smaller impact on the rate of income convergence; they raise the steady-state level of income inequality by 54%. Thus, the study presents strong evidence that neighbourhoods matter. These results, however, should be interpreted with some care, given that they are based on cross-sectional data from just one country. Obviously, any future research which either extends the analysis to another country or makes use of panel data is certainly worthwhile. However, the present study contributes to the literature on skill

formation and inequality in two ways. First, it presents a formal model of intergenerational mobility which allows expectations to vary across households. By assuming that expectations are influenced by both market and social forces, the analysis provides one possible explanation for levels of human capital investment differing across neighbourhoods (even after controlling for parental income). Second, the study reveals that social stratification matters because of its role in perpetuating income inequality across generations. To the extent that inequality reduces the rate of growth, the study provides one possible microeconomic explanation for the tendency of poor countries with large income disparities to grow more slowly than rich countries with greater levels of income equality.

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