Luxembourg Income Study Working Paper Series

Working Paper No. 158

Educational Streaming, Occupational Choice, and the Distribution of Wages

Kelly Bedard

April 1997

Luxembourg Income Study (LIS), asbl

Educational Streaming, Occupational Choice, and the Distribution of Wages

Kelly Bedard*
Department of Economics
McMaster University
Hamilton, Ontario
Canada, L8S 4M4

bedardk@mcmail.cis.mcmaster.ca

March 1997

ABSTRACT

This paper studies how the structure and quality of education influence occupational choices and the distribution of wages. Structure refers to the age at which children are streamed into specialized programs as well as the proportion of students placed in each stream. For example, the German education system is 'elitist'; the most academically gifted students are streamed into specialized programs at an early age. The Roy (1951) model of occupational choice is extended to incorporate the streaming of students into different programs based on academic ability prior to the point at which they self–select into an occupation. Streaming dates and the relative size of each stream have important implications for sectoral selection and the distribution of wages. Using German wage data and simulation techniques I show that educational policy changes may have a profound impact on certain groups of students. For example, admitting more students into the academic stream will significantly increase the wages of 'movers' who subsequently work in the white collar sector while lowering the wages of 'movers' who continue to work in blue collar jobs.

* I thank Chris Ferrall and Allan Gregory for helpful comments. I am responsible for all errors. I gratefully acknowledge financial support from the Canadian International Labour Network (CILN) at McMaster University and thank the Luxembourg Income Study for access to their database.

JEL Classification: I2, J3

Keywords: Education Systems, Wage Distributions

(1) Introduction

This paper extends the classic two skill Roy model of occupational choice studied by Roy (1951), Willis and Rosen (1979) and Heckman and Honore (1990) by incorporating the feedback mechanism (academic test scores) used by schools to stream students into different educational programs. Streaming refers to program placement that is determined by rules rather than self–selection. Educational streaming takes place before students are permitted to select an occupation, or in the Willis and Rosen (1979) environment, college participation. Simulations based on data from Germany are run to measure the potential impact of various educational policies on skill accumulation, occupational choice, and the distribution of wages.

Numerous papers have found that school quality and earnings are positively correlated (Welch, 1966; Morgan and Sirageldin, 1968; Johnson and Stafford, 1973; Wachtel, 1976; Rizzuto and Wachtel, 1980; Behrman and Birdsall, 1983; Card and Krueger, 1992). For example, Behrman and Birdsall (1983) find that students educated in Brazilian states providing high quality education earn higher wages than those educated in low quality states. Quality is proxied by average teacher education. Although this type of quality measure may not adequately reflect school quality differences in a modern developed economy, there is evidence to suggest that it may have been a reasonably good proxy in earlier times. For example, Card and Krueger (1992) find that American males born between 1920 and 1949 in states with high quality schools earn a higher return to a year of education than similarly aged individuals born in states with low quality schools.[1]

The link between school quality and test scores has been more hotly debated (see Hanushek (1986) for survey). During the 1960s and 1970s the U.S. experienced falling pupil–teacher ratios, rising expenditures, and plummeting SAT scores. This combination of events led many people to doubt the existence of a link between school quality and test scores. However, Betts (1994) and Ehrenberg and Brewer (1994) show that educational

[1] Quality is measured by pupil-teacher ratios, teacher wages, and term length.

quality has a positive impact on examination performance. Betts (1994) finds that homework and computer aided mathematics instruction positively influence math test scores. Ehrenberg and Brewer (1994) find that teacher quality positively affects the test score gain between sophomore and senior years.

Educational quality has implications for the full distribution of test scores and wages not simply the average. Brown and Saks (1975) show that the dispersion in reading and mathematics test scores may be related to pupil–teacher ratios and instructor quality even when average scores are not. Using data from eleven countries, Bedard and Ferrall (1997) find that streaming dates and the distribution of math test scores are related to the distribution of earnings later in life.

Educational streaming is a rarely studied, but potentially important element of educational policy. Both the age at which students are streamed into specialized programs and the proportion of students placed in each stream influence student outcomes. Although there are a variety of streaming structures, most education systems use some measure of academic ability to determine stream placement. Consider two polar examples. Country A is 'elitist'; they place the most academically gifted twenty–five percent of eleven year olds in the academic stream and relegate the remainder to the vocational stream. Country B is 'egalitarian'; children receive general education[2] until age fifteen, at which point the least academically talented quarter of the population are relegated to the vocational stream while the remainder of the population enter the academic stream. A student at the thirtieth percentile of the academic ability distribution spends his first five school years in a general program and the remaining seven in the vocational stream if he lives in the 'elitist' country, and ten years in a general program followed by two years in the academic stream if he lives in the 'egalitarian' country. Nationality clearly influences this individuals' final skill set which in turn affects his occupational opportunities and wage offers.

[2] During the pre–streaming, general education, phase both academic and vocational skills are augmented. As both skills receive some attention during this phase, it is assumed that the skill accumulation rate associated with any individual skill is slower than during the post–streaming period.

The model presented in this paper incorporates school quality, quantity, the age at which streaming occurs, and the proportion of students placed in each stream. This framework allows us to explore the timing and size of streams as well as focusing attention on more subtle stream composition issues. For example, stream size determines the mix of students in each stream. When academic ability is the lone streaming instrument, the smaller the pre–university stream the more homogeneous the group. This in turn influences the material that can be covered prior to secondary school graduation. Ehrenberg and Brewer (1994) find that mean test score gains between the sophomore and senior years are negatively affected by the presence of low achievers (defined as those scoring in the lowest quartile on the sophomore examination). Further, in a two stream system, the smaller the academic stream the larger, and less homogeneous the vocational stream. A one–dimensional streaming mechanism (academic test scores) exacerbates the heterogeneity problems inherent in a large vocational stream because it fails to take vocational ability into account. It is also important to remember that there is a trade–off between the potential for faster learning associated with more homogeneous streams, and the rigidity imposed by early streaming. Early streaming allows children to acquire more of a specific skill, but it also makes it more costly to switch streams, or occupations later in life.

Given the variety of educational structures that exist, and the influence that education has on earnings,[3] it is important to examine the institutions that children are exposed to before they are old enough to make their own academic and career choices. The education system a country selects profoundly affects the skills that children accumulate, the jobs they are offered, and the wages they receive.[4] Further, since education is a public policy

[3] Refer to surveys by Hanushek (1986) and Willis (1986), or papers by Welch (1966), Card and Krueger (1992), and Ashenfelter and Krueger (1994) for example.

[4] The importance of school structure and quality are diminished if students fail to attend or if the duration of attendance is prohibitively short. Bishop (1990) argues that American high school students perform poorly on mathematics and science tests because they are exposed to low quality schools and have low attendance rates. Lewis and Seidman (1994) show that the majority of the gap between American and Japanese math test scores can be explained by fewer American hours of mathematics instruction, less homework, and longer summer vacations.

instrument, some have argued that school policy should be used to pursue social objectives such as raising wages and reducing earnings inequality. Although these prescription may sound appealing, there is little evidence to suggest that the desired outcomes would necessarily result.

In order to quantify the impact of potential educational policy changes I use German wage data and simulation techniques to estimate underlying skill moments and school quality. I then use these moments to quantify the impact of various school policy changes for Germany. Indeed I find that simple policy prescriptions do not necessarily produce desirable results. For example, it has been suggested that Germany stream somewhat later to reduce some of the rigidity in the education system. While this tact will facilitate a better match between natural ability and occupations, since it is less costly to work in occupation that is unrelated to your post–stream training, the average wage level will be unaffected. This results because improved ability–occupation match for some is countered by a reduction in skill accumulation for others because skill accumulation is slower prior to streaming. This combination of lower skill accumulation and better ability–occupation match does however lead to less wage dispersion. It is quite clear that evaluating the impact of various educational policy changes requires an understanding of the impact that these policies have on specific types of students.

The remainder of this paper is organized as follows. Sections 2 and 3 describe the model and the distribution of skills and wages after educational streaming and occupational self–selection. The fourth section examines the impact of various school policy changes. Section 5 presents simulation results based on German data in order to quantify the potential influence exerted by such policy changes. Finally, section 5 summarizes and discusses possible extensions.

(2) The Model

Consider a two skill Roy model in which academic ability is the instrument used to divide the student population into two streams. Individuals are born with two occupation specific skill vectors, ε_{10} and $\varepsilon_{20} \geq 0$; these will be referred to as endowed, or innate skills. The vector $(ln\varepsilon_{10}, ln\varepsilon_{20})$ is assumed to be jointly normally distributed with finite mean (μ_1, μ_2) and variance Σ. Define $x_i = ln\varepsilon_{i0} - \mu_i$ for $i = 1, 2$, where $(x_1, x_2) \sim N(0, \Sigma)$.

The early stages of education focus on the development of a wide variety of motor and intellectual skills. It is therefore assumed, without loss of generality, that both skills are augmented equally during this educational phase.[5] At the conclusion of the general education stage, which occurs at an age chosen by educators, students are separated into two streams. The academic stream (stream 1) augments ε_{10} exclusively from this point forward, while the vocational stream (stream 2) augments only ε_{20}. All students graduate with skills:

$$\varepsilon_{12} = e^{S_1} e^{S^*_{12}(\varepsilon_{10})} \varepsilon_{10}$$

$$\varepsilon_{22} = e^{S_1} e^{S^*_{22}(\varepsilon_{10})} \varepsilon_{20}.$$

S_1 denotes the augmenting factor for pre–stream training. The augmenting factors associated with post–stream training depend on stream membership.[6]

$$S^*_{12}(\varepsilon_{10}) = \begin{cases} S_{12} & \text{if } \varepsilon_{10} \geq k \\ 0 & \text{if } \varepsilon_{10} < k \end{cases}$$

$$S^*_{22}(\varepsilon_{10}) = \begin{cases} 0 & \text{if } \varepsilon_{10} \geq k \\ S_{22} & \text{if } \varepsilon_{10} < k \end{cases}$$

where k is the critical value for placing the least academically gifted δ% of the population in the vocational stream.

The model abstracts from high school drop-outs; all students complete the education phase. Academic and vocational training are also assumed to be of the same duration.

[5] This assumption is made for expositional ease. Allowing the skills to be augmented at different rates does not qualitatively alter the results.

[6] The school terms are restricted to be non–negative; education is assumed to have a positive affect on final skill levels.

Time spent in school augments initial skills with weight θ, which is a multiplicative function of educational quality and quantity. Given the above structure, $2S_1 + S_{12}^*(\varepsilon_{10}) + S_{22}^*(\varepsilon_{10}) = \theta$.[7] The proportion of total education acquired prior to streaming is v, therefore, $S_1 = \frac{v\theta}{2}$. Similarly, the proportion of time spent in school after streaming is $(1 - v)$, which means that $S_{i2} = (1 - v)\theta$ for each stream i.

Innate ability and the skills accumulated in school are subsequently put to use in one of two sectors. White collar jobs require only academic skill, and blue collar occupations use only vocational skills. Each skill has an associated skill price π_i for $i = 1, 2$. Therefore, the sector specific earnings functions are:

$$W_1 = \pi_1 e^{S_1} e^{S_{12}^*(\varepsilon_{10})} \varepsilon_{10}$$

$$W_2 = \pi_2 e^{S_1} e^{S_{22}^*(\varepsilon_{10})} \varepsilon_{20}.$$

Taking logarithms and redefining variables,

$$w_1 = p_1 + v\theta/2 + \mu_1 + S_{12}^*(\varepsilon_{10}) + x_1$$

$$w_2 = p_2 + v\theta/2 + \mu_2 + S_{22}^*(\varepsilon_{10}) + x_2$$

where: $w_i = lnW_i$ and $p_i = ln\pi_i$, for $i = 1, 2$.

At the conclusion of the education phase, people choose to work in the sector offering them the highest wage:

$$w = max\{w_1, w_2\}.$$

The condition for choosing white collar (sector 1) employment, $w_1 \geq w_2$, implies that $a_1 + x_1 \geq x_2$, where $a_1 = (p_1 - p_2) + (\mu_1 - \mu_2) + (1 - v)\theta$, for academic stream members, and that $a_2 + x_1 \geq x_2$, where $a_2 = (p_1 - p_2) + (\mu_1 - \mu_2) - (1 - v)\theta$, for those educated in the vocational stream. Similarly, the conditions for choosing blue collar employment are $a_1 + x_1 < x_2$ and $a_2 + x_1 < x_2$ for academic and vocational stream members respectively.

[7] The total benefit of education, θ, is the same across individuals because program quality and duration are identical across streams. This assumption can be weakened without altering the qualitative results of the model.

(3) The Distribution of Skills and Wages After Streaming and Self–Selection

The conditional intra–stream–sector moments are calculated using a method similar to that of Tallis (1961) and Muthen (1990) with the addition of self–selection. The problem is broken into white and blue collar sectors and academic and vocational streams. There are four education–sector groups: stream 1 – sector 1, stream 2 – sector 1, stream 1 – sector 2, and stream 2 – sector 2, these groups are numbered 1 through 4 respectively for expositional ease. For example, group 1 (stream 1 – sector 1) contains people educated in the academic stream who subsequently choose white collar employment. A moment generating function (MGF) is used to calculate the moments for each education–sector group.

The MGF for the bivariate normal distribution with mean 0 and variance Σ, which incorporates truncation and self–selection is:

$$\Pi_{ij} M_{ij} = exp(T) \int_{g_1-\tau_1}^{h_1-\tau_1} \int_{g_2-\tau_2}^{h_2-\tau_2} \phi(x_1, x_2) dx_2 dx_1$$

where i = educational stream, j = sector, $T = (1/2)(\sigma_1^2 t_1^2 + 2\rho\sigma_1\sigma_2 t_1 t_2 + \sigma_2^2 t_2^2)$, $\tau_1 = \sigma_1^2 t_1 + \rho\sigma_1\sigma_2 t_2$, and $\tau_2 = \rho\sigma_1\sigma_2 t_1 + \sigma_2^2 t_2$. Educational stream placement determines the value of h_1 and g_1. Self–selection is incorporated in either h_2 or g_2, depending on the conditional moment of interest. For example, stream 2 students choosing employment in the white collar sector (group 2): $g_1 = k$, $h_1 = -\infty$, $g_2 = -\infty$, and $h_2 = a_2 + x_1$. The moment generating functions for each group are in Appendix A. Throughout this paper $\phi()$ denotes the bivariate normal density function with mean 0 and variance Σ, $f()$ denotes the standard univariate normal density function, and $F()$ denotes the standard univariate normal cumulative density function.

The probability of being educated in the academic stream and then choosing to work in the white collar sector is:

$$\Pi_{11} = \int_{k}^{\infty} \int_{-\infty}^{a_1+x_1} \phi(x_1, x_2) dx_2 dx_1.$$

The MGF for innate skills is:

$$\begin{aligned} \Pi_{11}M_{11} &= \int_{k-\tau_1}^{\infty}\int_{-\infty}^{a_1+x_1-\tau_2} \phi(x_1,x_2)dx_2dx_1 \\ &= exp(T)\sigma_1^{-1}\int_{k-\tau_1}^{\infty} f(x_1/\sigma_1)F\Big[\Big(\frac{a_1+x_1-\tau_2}{\sigma_2} - \rho\frac{x_1}{\sigma_1}\Big)c\Big]dx_1 \end{aligned}$$

where $c = (1-\rho^2)^{-1/2}$. The conditional mean is the derivative of the MGF with respect to t_1 evaluated at $t_1 = t_2 = 0$.

$$\begin{aligned} E(x_1|G_1) &= \Pi_{11}^{-1}\Big\{\sigma_1 f(k/\sigma_1)F(A_1) - \rho c\int_k^{\infty} f(x_1/\sigma_1)F(B_1)dx_1\Big\} \\ E(w_1|G_1) &= p_1 + \mu_1 + \theta - \frac{\theta v}{2} + E(x_1|G_1) \end{aligned}$$

where $G_1 = (x_1 \geq k, w_1 > w_2)$, $G_2 = (x_1 < k, w_1 > w_2)$, $G_3 = (x_1 \geq k, w_2 > w_1)$, $G_4 = (x_1 < k, w_2 > w_1)$, $A_i = (\frac{a_i+k}{\sigma_2} - \rho\frac{k}{\sigma_1})c$, and $B_i = (\frac{a_i+x_1}{\sigma_2} - \rho\frac{x_1}{\sigma_1})c$, for $i = 1,2$. The conditional variance is the second derivative of the MGF with respect to t_1 evaluated at $t_1 = t_2 = 0$.

$$\begin{aligned} Var(w_1|G_1) = \sigma_1^2 + \Pi_{11}^{-1}\sigma_1\Big\{& kf(k/\sigma_1)F(A_1) - \rho\sigma_1^3 cf(k/\sigma_1)f(A_1) \\ & - \rho^2c^2\int_k^{\infty} B_1 f(x_1/\sigma_1)f(B_1)dx_1\Big\} - E(x_1|G_1)^2 \end{aligned}$$

The conditional means and variances for the remaining three stream-sector groups are obtained in the same manner in Appendix A.

If there is no streaming the model collapses to the standard Roy (1951) model, with the addition of a school quality term. In the standard self–selection model the distribution of skills has a simple bivariate nature. Individuals face a blue collar and a white collar wage offer that depend on skill prices and their final skill levels.[8] Each worker simply accepts the highest wage offer. In the present environment, the highest wage offer continues to determine sectoral selection, however, educational streaming forces a wedge into the final

[8] If education augments both skills at the same rate then sectoral selection depends on innate skills and the relative skill price.

skill distribution. Accounting for years of education, as is done in standard empirical work does not fully disentangle innate and final skills.

In the Willis and Rosen (1979) environment, an individual chooses to attend college if his expected lifetime income stream from doing so exceeds the expected return from stopping with a high school diploma. Their estimates show that a positive selection bias exists in the earnings of both high school graduates and those with a college education. In other words, an individual who chooses not to attend college has better prospects with that designation than the average person who attends college. Conversely, a student choosing to enroll in college has better prospects with a university education than the average high school graduate.

Extending the Willis and Rosen framework to include school streaming changes the story significantly. Even abstracting from the issue of school quality, school quantity no longer adequately describes an individuals' educational experience. For example, one student may spend the majority of his educational career in vocational classes while another participates in a pre–university stream. In addition to their innate ability differences these individuals also augment their skills differently. Even in the event that innate abilities are positively related, skills measured at graduation may be negatively correlated because school streaming forces students to augment skills unevenly.

The point at which skills are assumed to be given is the pivotal issue. Assume for convenience that the two occupation specific skills are normally distributed at birth, and that the education system then augments these skills in a specific way. If the education system employs any form of streaming the unaccounted for institutional structure will bias the skill correlation estimate downward. Unaccounted for quality differences will further bias the unobservable skill correlation estimates downward. Consider the impact of concentrating middle and upper class children in a few schools. If schools are locally funded, as in the United States, children living in prosperous school districts will attend more high quality institutions, and augment innate skills at a faster rate.

Lemma 1 *(i) If skills are positively correlated the mean stream 2 vocational skill endowment is lower than the mean population skill endowment. (ii) In the event that the vocational stream is sufficiently small relative to innate academic skill variance, the stream 2 vocational skill variance exceeds that of the entire population. (iii) In all other cases stream specific mean skill endowments are at least as great as those of the population while the variances are smaller.*

Proof *All proofs are provided in Appendix A.*

The one dimensional tracking rule guarantees that stream 1 contains the academic elite, but makes no such assurance with respect to the vocational stream. As stream 1 is constructed to be the high academic ability subset, the academic skill mean is necessarily higher than that of the entire population and its variance is lower. If skills are uncorrelated both the stream 2 vocational skill mean and variance are identical to the population mean and variance. In this case, routing the academic elite into stream 1 has no impact on the stream 2 vocational skill distribution. On the other hand, negative skill correlation is sufficient to ensure that the stream 2 vocational skill mean exceeds that of the population, while positive correlation guarantees the reverse. Finally, under most conditions, the stream 2 vocational skill variance is smaller than that of the population. Note that this is guaranteed if at least half the population belongs to the vocational stream. In order for the relative magnitudes to be reversed the vocational stream must be sufficiently small, as defined by Lemma 1, relative to the variance of academic skills.

Lemma 2 *Under negative skill correlation, the relevant skill level of those choosing to work in the sector for which they are trained exceeds that of the population at large. Conversely, under positive skill correlation the average academically trained blue collar worker possesses a higher than average vocational skill endowment while the average vocationally trained white collar worker has a lower than average academic skill endowment.*

Average group skill levels are more complicated than the stream means because they depend on both educational decisions and occupational choices. The interaction between forced school programs and sectoral selection is important. Non–positive skill correlation ensures that those opting to work in the sector for which they are trained possess higher than average relevant skills. This results because streaming and self–selection reinforce one another. On average schools make the correct placement decision and individuals subsequently choose employment based on their skill levels at graduation. The mean relevant skill levels of 'cross–over' groups, those choosing to work in the sector for which they are not trained, can only be unambiguously compared to that of the population under non–negative skill correlation. In this case, the most academically and vocationally talented stream 2 members form group 4, which ensures that the group 2 academic skill mean falls short of the cohort average. Conversely, although self–selection encourages the most academically gifted stream 1 students to join group 1, positive skill correlation ensures that the group 3 vocational skill mean exceeds that of the population at large.

The asymmetry in the streaming mechanism is not without consequence. Reliance on a one–dimensional tracking rule means that some people are improperly streamed. An individual who is sufficiently academically gifted is placed in stream 1 even if he is relatively more vocationally gifted. Alternatively, a weak academic student is relegated to the vocational stream, even if she would benefit more from academic training.

The form of the streaming rule generates an environment in which knowledge regarding the skill correlation direction is sufficient to compare the relevant stream specific skill averages to those of the population. However, comparing the stream–sector group and population skill averages often requires more detailed information about the initial conditions. Under certain skill and education conditions, even those working in the 'correct' sector may exhibit an average skill level below the population mean. The complex interaction between innate ability, school structure, and occupational choice ensures a wide range of possible outcomes.

(4) Educational Policy Changes

Education policy changes affect each stream–sector group differently. Accelerating the streaming date may, under certain conditions, lower the group 2 mean wage, raise the group 1 mean wage, and increase the dispersion within both groups. Similarly, a policy may decrease overall wage dispersion in one environment while causing it to increase under a different set of initial conditions. The interaction between variables makes it difficult to sign the comparative statics without a significant quantity of knowledge regarding the initial environment. While group size changes can be evaluated, it is generally impossible to sign first and second wage moment comparative statics because the skill composition of 'movers' is unknown.

Proposition 1 *Increasing the proportion of students placed in the vocational stream increases the the average wage of the academically educated who choose white collar employment.*

The intution behind this result is very simple. Increasing the size of the vocational stream is accomplished by moving the least academically gifted students from the academic stream to the vocational stream. The new smaller group of academically trained white collar workers therefore possesses a higher mean academic skill endowment, and subsequently enjoys a higher average white collar wage.

Although, under certain conditions, it is possible to determine the impact that a change in the vocational stream size has on group 1 and 2 mean wages, it is difficult to specify conditions sufficient to determine the overall affect on the average white collar wage. For example, $\rho \leq 0$, $k \leq 0$, and $f(A_1) \geq f(A_2)$ ensures that an increase in the vocational stream size increases the average white collar academic skill endowment. However, a mover who continues to choose sector 1 employment does so with less academic training, and a lower sector 1 wage. The average white collar academic skill endowment therefore rises while the mean level of academic training falls, rendering the overall effect ambiguous.

Proposition 2 *The overall average wage falls as the proportion of students placed in the vocational stream rises if* $k \geq 0$, $(p_1 - p_2) + (\mu_1 - \mu_2) \geq 0$, $\rho \leq 0$, $\sigma_1 \geq \sigma_2$, $F(A_1) + F(A_2) \geq 1$, *and* $f(A_1) \leq f(A_2)$.

If the vocational stream contains more that fifty percent of the students, further increasing the size of that stream decreases the overall average wage when the requirements of Proposition 2 are satisfied. The requirements ensure that the gain enjoyed by 'movers' choosing the blue collar sector are dominated by the losses incurred by those who continue to opt for white collar employment. Having stated the conditions sufficient to ensure that the overall average wage falls, it is important to note that this outcome depends heavily on the initial environment. Under different initial conditions the benefit to the 'movers' who become members of group 4 may dominate the losses incurred by group 2 joiners. In this case the the average wage will rise.

(5) Simulation of Policy Changes for Germany

A more detailed examination of the impact that school policy changes have on various conditional wage moments requires substantial information regarding the underlying skill distributions and prices. In this section I use simulation techniques and German wage data to estimate the first two skill moments. I then use these skill moments to quantify the impact that specific school policy changes have on future career decisions and the distribution of skills and wages.

The wage data used in this simulation is 1984 *Wave II: German Panel Survey* data from the Luxembourg Income Study. The sample includes 429 full–time, civilian, married, non–disabled, male workers aged 35 to 44 who report some form of occupational training. The academic stream is defined as college/engineering, university, or public service training, and the vocational stream includes all trade, commercial, and vocational training programs. The 1984 *Wave II: German Panel Survey* provides relatively detailed information about worker type. Blue and white collar occuaptions are clearly defined. Refer to Appendix B for a full description of the data; including education stream and occupation definitions.

The sample moments for the four education–occupation groups are matched with the simulated moments by minimizing the weighted sum of the absolute distances between the sample and simulated group sizes, means, and standard deviations using simulated annealing.[9] The vocational stream size (k) and the time of streaming (v) are known. There are no calibrated parameters. I estimate the value of seven parameters: two school quality parameters, skill means, and skill variances, as well as the covariance between skills.[10] In order to better match the simulated and sample moments the model is generalized to allow academic and vocational quality/quantity parameters to differ. These parameters are denoted θ_1, and θ_2 respectively. I continue to assume that pre–stream schooling augments each skill at half the post–stream rate.

Table 1. Sample and Simulated Log Wage Moments

	Proportion in Group		Mean		Standard Deviation	
	Sample	Simulated	Sample	Simulated	Sample	Simulated
Group 1	0.29	0.29	10.98	11.14	0.30	0.30
Group 2	0.32	0.32	10.85	10.38	0.28	0.26
Group 3	0.01	0.01	10.83	11.01	0.17	0.15
Group 4	0.38	0.39	10.57	10.29	0.24	0.39

This simple model does a surprisingly good job of matching the sample moments. As might be expected, matching the blue collar wage moments is the most problematic. This difficulty most likely arises because the model does not allow for wage compression due to unionization. As unions are particularly powerful in the blue collar sector, it is not

[9] The distances between sample and simulated moments are weighted by the inverse of the sample moment. Due to the smallness of group 3, I exclude all moments above group size for group 3 when matching the moments.

[10] Log skill prices are normalized to 0.

surprising that a model that does not incorporate union wage setting institutions has more difficulty matching these wage moments.[11]

The estimated correlation between endowed skills is 0.59. This means that a substantial proportion of students are mis–streamed, as compared to an education system that use a streaming rule that is based on both skills and the relative skill price.[12] In the present environment this is equivalent to self–selected streaming. Based on the estimates presented in Table 2, 50% of vocational stream students would be better served by academic training. On the other hand, post–stream vocational training would be preferable for only 3% of academic stream students. Stream placement errors are rare among academic stream students because membership is very selective, is dependent on academic ability, and because there is an academic skill price premium.

Table 2. Estimated Skill Parameters

academic quality (θ_1)	0.06
vocational quality (θ_2)	0.10
skill 1 mean (μ_1)	10.40
skill 2 mean (μ_2)	10.21
skill 1 variance (σ_{11})	0.33
skill 2 variance (σ_{22})	0.12
covariance (σ_{12})	0.12
skill correlation (ρ)	0.59

Although the correlation between innate academic and vocational skills is 0.59, the correlation between final skills is only 0.56. One might expect the difference between these two correlations to be greater since uneven skill accumulation puts downward pressure on the correlation between final skills. The relative closeness of the two correlations results

[11] It is possible, however, to extend the model presented in this paper to allow for unionization. In Bedard and Roberts (1997) we generalize the present model to allow both students and teachers to be uncertain about student abilities. This uncertainty leads to stream placement errors, and if students are risk averse the possibility that students will choose to join a unionized sector to insure themselves against their uncertainty regarding there abilities.

[12] The degree of mis–streaming diminishes as the correlation between skills falls and becomes negative.

because the skill augmenting power of education is not particularly large. The distance between the innate and final skill correlations would be greater in an environment with a more powerful (effective) education system.

Given the estimated skill parameters we can simulate school policy changes and examine the impact on the distribution of skills and wages. Table 3 presents the wage moments for the entire labour force, the white collar sector, and the blue collar sector under various school policy changes. The school policy changes presented in this table are large in magnitude: switching to a vocational stream that only contains 30% of the population, doubling school effectiveness, streaming 25% later, and using a two–dimensional streaming rule (self–selection). Despite the apparent grandeur of the various policy changes, only doubling school effectiveness has a large impact on the presented wage moments. The insensitivity of the wage moments to educational policy changes stems from three sources: the ineffectiveness of education, the fact that most policy changes have winners and losers, and the ability of students to opt for employment in the sector offering the highest wage. Quantifying the influence exerted by school policy changes therefore requires measuring the gains and losses experienced by the winning and losing groups.

Table 3. Selected School Policy Changes

		Base Case	Str. 2 = 30%	2× School Quality	Str. Date = 75%	Self–Sel. Str.
Overall	Mean Wage	10.55	10.55	10.60	10.55	10.56
	Std. Dev Wage	0.48	0.47	0.47	0.47	0.47
White Collar Sector	Sector Size	0.61	0.65	0.57	0.63	0.63
	Mean Wage	10.72	10.72	10.79	10.71	10.72
	Std. Dev Wage	0.47	0.46	0.48	0.47	0.46
Blue Collar Sector	Sector Size	0.39	0.35	0.43	0.37	0.37
	Mean Wage	10.28	10.25	10.35	10.27	10.29
	Std. Dev Wage	0.34	0.34	0.33	0.34	0.35

Inverting the stream sizes so that the vocational stream contains 30% of the population means that 40% of the population will change streams. More precisely, the most academically gifted 57% of the vocational stream will now enter the academic stream. 71% of 'movers' will go on to earn a higher wage. Not surprisingly, the 'movers' who benefit the most from the policy change are those who were previously educated in the vocational stream and then switched to the white collar sector (group 3). However, 33% of 'movers' were originally group 4 members, and 88% of these 'movers' earn a lower wage after the policy change. This group of 'movers' suffers the largest wage loss, their average log wage falls from 10.57 to 10.52.

High quality education raises the wages of individuals opting for employment in the sector for which they are trained and makes 'cross–over' employment costly. An increase in school quality will therefore encourage more people to work in the 'correct' sector. Under the estimated skill parameters, doubling both academic and vocational training effectiveness, will lead 4% more people to work in 'correct' sector.[13] A school quality increase of this magnitude has a large impact on the entire wage distribution. The mean log wage rises from 10.55 to 10.60. It is important to note however, that higher school quality necessarily increases the final skill set of the more able to a greater degree than the less able because school effectiveness enters multiplicatively (in levels).

Doubling only one of the school effectiveness parameters has much different repercussions. A change of this nature does not encourage anyone to change education–occupation paths, but it does effect the distribution of wages. Doubling academic school quality increases the mean log wage to 10.57 and the standard deviation to 0.48. Wage variance rises because the school quality increase is only relevant for the group that is already enjoying a skill price premium. Conversely, doubling vocational school quality increases the mean log wage to 10.58 and lowers the standard deviation to 0.46. The impact on the mean wage is larger simply because the vocational stream is larger.

[13] 98% of these people move from group 3 to group 4.

Decelerating the streaming date from $v = 0.50$ to $v = 0.75$ has very little effect on the distribution of wages. However, later streaming does facilitate somewhat better sorting along skill lines. The mean (relevant) innate skill level rises by 2% for group 1 and 10% for group 4 and falls by 3% and 11% for groups 2 and 3 respectively. The group 4 (group 2) mean academic skill rise (fall) results because decreased skill accumulation heightens the importance of relative skill prices and entices individuals with lower academic skills, and because skills are positively correlated lower vocational skills as well, into the white collar sector. Despite the small increase in education–occupation path switching, only 2% more people work in the 'wrong' sector, the mean wage falls only slightly. This occurs because individuals choosing to work in the sector for which they are trained now earn a slightly lower wage while people choosing the 'cross–over' sector now earn slightly more.

In order to quantify the inefficiency inherent in a one–dimensional streaming rule, the final column of table 3 presents selected simulated German wage moments under self–selected streaming. The small changes in sectoral wage moments are deceptive in the sense that they mask the off–setting wage changes occurring within certain education–occupation groups. All white collar workers who were educated in the vocational stream will now enter the academic stream. This increases the mean log wage for this group from 10.36 to 10.39. Similarly, all group 2 members will switch to the vocational stream thereby increasing the mean log wage for this group from 10.99 to 11.04. In contrast, only 1% and 6% of groups 1 and 4 will switch to the other stream. Therefore, the population wage moments change very little because the wage gains enjoyed by the 'movers' are tempered by the stationary wages of 'non–movers' (64% of the population).

The structure of the education system clearly affects the skills that students accumulate while in school and the opportunities available to them upon graduation. Students placed in the 'wrong' stream (who have a relative advantage in the other skill) receive sub–optimal training and subsequently receive a lower wage. A one–dimensional streaming rule has particularly grave consequences when skills are strongly positively correlated.

In this case, the streaming rule forces good academic students into the academic stream despite their relative vocational advantage.[14] More importantly, the streaming rule forces too many people into the vocational stream; people with a comparative academic advantage. The inefficiency associated with a one–dimensional streaming rule rises with the academic skill price premium and the vocational stream size. A country with a one–dimensional streaming rule that forces a large percentage of the population into the vocational stream (like Germany) ends up with a large number of people working in the 'wrong' sector. For example, when the vocational stream contains 70% of the student body, 36% of the population subsequently work in the 'wrong' sector, while only 19% of the population go on to work in the 'wrong' sector when the vocational stream contains only 30% of students. From the opposite perspective, one might argue that it is not that too many people choose the 'wrong' sector, but rather that too many people are educated in the 'wrong' stream.

(6) Conclusion

The simple framework developed in this paper demonstrates the complexity of the relationship between school structure, occupational choice, and the distribution of wages. When considering the role that school policy plays in determining the distribution of wages it is important to remember that over the course of an individual's life some decisions are forced while others are freely chosen. Therefore, a school policy change that is intended to increase worker productivity may also encourage some students to make different career choices. The interaction between these forced and freely chosen decisions determines the impact that school policy changes have on the distribution of earnings.

The inter–play between teacher and student decisions guarantees that the skill accumulation and occupational selection changes resulting from a school policy change will depend heavily on the initial environment. In the absence of detailed information about the underlying distribution of skills and educational structure, the only thing that can be

[14] This problem is largely mitigated if there is an academic skill price premium.

said with certainty is that decreasing the size of the academic stream raises the average wage of white collar workers who were educated in the academic stream. This result is ensured by the one–dimensional streaming rule.

However, armed with detailed information about the distribution of skills and the underlying educational structure, section 5 documents the potential influence exerted by various school policy changes for Germany. Moving towards more self–selected streaming or higher quality schools will increase mean wages and decrease variance in Germany. In contrast, decelerating the streaming date or increasing academic stream admission will have little impact on mean wages, but will lead to lower variance.

The framework developed in this paper can be extended in several ways. First, although the model is cast in an occupational choice framework, it could be recast as one of higher education choice. Second, this paper assumes that academic ability is perfectly measured, and that the one–dimensional streaming rule can therefore be applied without error. Generalizing the present streaming rule to incorporate the notion that program placement errors are more acute the earlier streaming occurs, would allow us to examine the trade–off between the more rapid post–stream skill accumulation and the costs associated with inaccurate streaming.

References

[1] Allen, Jeremiah and Roger Barnsley (1993), "Streaming and Tiers: The Interaction of Ability, Maturity, and Training in Systems with Age-Dependent Recursive Selection," *Journal of Human Resources*, 28(3), 649-659.

[2] Ashenfelter, Orley and Alan Krueger (1994), "Estimates of the Economic Return to Schooling from a New Sample of Twins," *American Economic Review*, 84(5), 1157-1173.

[3] Bedard, Kelly and Chris Ferrall (1997), "Test Scores and Wage Inequality: Some International Evidence," manuscript, Queen's University.

[4] Bedard, Kelly and Joanne Roberts (1997), "Acquiring Skills and Insurance Through Education," manuscript, McMaster University.

[5] Behrman, Jere and Nancy Birdsall (1983), "The Quality of Schooling: Quantity Alone is Misleading," *American Economic Review*, 73(5), 928- 946.

[6] Betts, Julian (1994), "Inside the Classroom: New Evidence on the School Quality Debate," manuscript, University of California, San Diego.

[7] Bishop, John (1990), "Incentives for Learning: Why American High School Students Compare so Poorly to their Counterparts Overseas," *Research in Labor Economics*, 11, 17-51.

[8] Brown, Byron and Daniel Saks (1975), "The Production and Distribution of Cognitive Skills within Schools," *Journal of Political Economy*, 83(3), 571-593.

[9] Ehrenberg, Ronald and Dominic Brewer (1994), "Do School and Teacher Characteristics Matter? Evidence from High School and Beyond," *Economics of Education Review*, 13(1), 1-17.

[10] Hanushek, Eric (1986), "The Economics of Schooling: Production and Efficiency in Public Schools," *Journal of Economic Literature*, 24(September), 1141-1177.

[11] Heckman, James and Bo Honore (1991), "The Empirical Content of the Roy Model," *Econometrica*, 58(5), 1121-1149.

[12] Heckman, James and Guilherme Sedlacek (1985), "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self- Selection in the Labor Market," *Journal of Political Economy*, 93(6), 1077-1125.

[13] Heckman, James and Guilherme Sedlacek (1990), "Self-Selection and the Distribution of Hourly Wages," *Journal of Labor Economics*, 8(1), S329-S363.

[14] Johnson, George and Frank Stafford (1973), "Social Returns to Quantity and Quality of Schooling," *Journal of Human Resources*, 8(Spring), 139-155.

[15] Lewis, Kenneth and Laurence Seidman (1994), "Math-Time Capital Matters: A Cross-Country Analysis," *Economics of Education Review*, 13(3), 215-226.

[16] Morgan, James and Ismail Sirageldin (1968), "A Note on the Quality Dimension in Education," *Journal of Political Economy*, 76(September/October), 1069-1077.

[17] Muthen, Bengt (1990), "Moments of the Censored and Truncated Bivariate Normal Distribution," *British Journal of Mathematical and Statistical Psychology*, 43, 131-143.

[18] Rizzuto, Ronald and Paul Wachtel (1980), "Further Evidence on the Returns to School Quality," *Journal of Human Resources*, 15(Spring), 240-254

Appendix A

First and Second Moments

Sections A1 through A4 contain the probability of the specified group, the MGF for endowed skills, and first two wage moments for each of the four education-sector groups.

(A1) Stream 1 - Sector 1 (Group 1)

The probability of being educated in the academic stream and then choosing employment in the white collar sector:

$$\Pi_{11} = \int_{k}^{\infty} \int_{-\infty}^{a_1+x_1} \phi(x_1, x_2) dx_2 dx_1.$$

The MGF for endowed skills:

$$\Pi_{11} M_{11} = exp(T) \int_{k-\tau_1}^{\infty} \int_{-\infty}^{a_1+x_1-\tau_2} \phi(x_1, x_2) dx_2 dx_1.$$

The first two wage moments for Group 1:

$$\begin{aligned} E(w_1|G_1) &= p_1 + \mu_1 + \theta - \frac{\theta v}{2} + E(x_1|G_1) \\ &= p_1 + \mu_1 + \theta - \frac{\theta v}{2} + \Pi_{11}^{-1} \Big\{ \sigma_1 f(k/\sigma_1) F(A_1) - \rho c \int_{k}^{\infty} f(x_1/\sigma_1) f(B_1) dx_1 \Big\} \\ V(w_1|G_1) &= \sigma_1^2 + \Pi_{11}^{-1} \sigma_1 \Big\{ k f(k/\sigma_1) F(A_1) - \rho \sigma_1^3 c f(k/\sigma_1) f(A_1) - \rho^2 c^2 \int_{k}^{\infty} B_1 f(x_1/\sigma_1) f(B_1) dx_1 \Big\} \\ &\quad - E(x_1|G_1)^2. \end{aligned}$$

$\rho \leq 0$ is sufficient to ensure that $E(x_1|G_1) \geq 0$, $E(w_1|G_1) \geq 0$, and $E(w_1|G_1) \geq E(w_1|streaming, random\ occupational\ assignment)$, where $E(w_1|streaming, random\ occupational\ assignment) = p_1 + \mu_1 + \sigma_1^{-1}[1 - F(k/\sigma_1)](1-v)\theta$.

(A2) Stream 2 - Sector 1 (Group 2)

The probability of being educated in the vocational stream and then choosing employment in the white collar sector:

$$\Pi_{21} = \int_{-\infty}^{k} \int_{-\infty}^{a_2+x_1} \phi(x_1, x_2) dx_2 dx_1.$$

The MGF for endowed skills:

$$\Pi_{21} M_{21} = exp(T) \int_{-\infty}^{k-\tau_1} \int_{-\infty}^{a_2+x_1-\tau_2} \phi(x_1, x_2) dx_2 dx_1.$$

The first two wage moments for Group 2:

$$\begin{aligned} E(w_1|G_2) &= p_1 + \mu_1 + \frac{\theta v}{2} + E(x_1|G_2) \\ &= p_1 + \mu_1 + \frac{\theta v}{2} - \Pi_{21}^{-1} \Big\{ \sigma_1 f(k/\sigma_1) F(A_2) + \rho c \int_{-\infty}^{k} f(x_1/\sigma_1) f(B_2) dx_1 \Big\} \\ V(w_1|G_2) &= \sigma_1^2 - \Pi_{21}^{-1} \sigma_1 \Big\{ k f(k/\sigma_1) F(A_2) - \rho \sigma_1^3 c f(k/\sigma_1) f(A_2) + \rho^2 c^2 \int_{-\infty}^{k} B_2 f(x_1/\sigma_1) f(B_2) dx_1 \Big\} \\ &\quad - E(x_1|G_2)^2. \end{aligned}$$

$\rho \geq 0$ is sufficient to ensure that $E(x_1|G_2) \leq 0$.

(A3) Stream 1 - Sector 2 (Group 3)

The probability of being educated in the academic stream and then choosing employment in the blue collar sector:

$$\mathit{\Pi}_{12} = \int_{k}^{\infty} \int_{a_1+x_1}^{\infty} \phi(x_1, x_2) dx_2 dx_1.$$

The MGF:

$$\mathit{\Pi}_{12} M_{12} = exp(T) \int_{k-\tau_1}^{\infty} \int_{a_1+x_1-\tau_2}^{\infty} \phi(x_1, x_2) dx_2 dx_1.$$

The first two wage moments for Group 3:

$$\begin{aligned} E(w_2|G_3) &= p_2 + \mu_2 + \frac{\theta v}{2} + E(x_2|G_3) \\ &= p_2 + \mu_2 + \frac{\theta v}{2} + \mathit{\Pi}_{12}^{-1}\sigma_2\Big\{\rho f(k/\sigma_1)[1 - F(A_1)] + c\sigma_1^{-1} \int_{k}^{\infty} f(x_1/\sigma_1) f(B_1) dx_1\Big\} \\ V(w_2|G_3) &= \sigma_2^2 + \mathit{\Pi}_{12}^{-1}\sigma_2^2\Big\{\rho^2\sigma_1^{-1} k f(k/\sigma_1)[1 - F(A_1)] + \rho^2 c(\sigma_1\sigma_2 - \rho) f(k/\sigma_1) f(A_1) + \rho c f(k/\sigma_1) f(A_1) \\ &\quad + c^2\sigma_1^{-1} \int_{k}^{\infty} B_1 f(x_1/\sigma_1) f(B_1) dx_1\Big\} - E(x_2|G_3)^2. \end{aligned}$$

$\rho \geq 0$ is sufficient to ensure that $E(x_2|G_3) \geq 0$.

(A4) Stream 2 - Sector 2 (Group 4)

The probability of being educated in the vocational stream and then choosing employment in the blue collar sector:

$$\mathit{\Pi}_{22} = \int_{-\infty}^{k} \int_{a_2+x_1}^{\infty} \phi(x_1, x_2) dx_2 dx_1.$$

The MGF:

$$\mathit{\Pi}_{22} M_{12} = exp(T)\sigma_1^{-1} \int_{-\infty}^{k-\tau_1} \int_{a_2+x_1-\tau_2}^{\infty} \phi(x_1, x_2) dx_2 dx_1.$$

The first two wage moments for Group 4:

$$\begin{aligned} E(w_2|G_4) &= p_2 + \mu_2 + \theta - \frac{\theta v}{2} + E(x_2|G_4) \\ &= p_2 + \mu_2 + \theta - \frac{\theta v}{2} - \mathit{\Pi}_{22}^{-1}\sigma_2\Big\{\rho f(k/\sigma_1)[1 - F(A_2)] - c\sigma_1^{-1} \int_{-\infty}^{k} f(x_1/\sigma_1) f(B_2) dx_1\Big\} \\ V(w_2|G_4) &= \sigma_2^2 - \mathit{\Pi}_{22}^{-1}\sigma_2^2\Big\{\rho^2\sigma_1^{-1} k f(k/\sigma_1)[1 - F(A_2)] - \rho^2 c(\sigma_1\sigma_2 - \rho) f(k/\sigma_1) f(A_2) - \rho c f(k/\sigma_1) f(A_2) \\ &\quad + c^2\sigma_1^{-1} \int_{-\infty}^{k} B_2 f(x_1/\sigma_1) f(B_2) dx_1\Big\} - E(x_2|G_4)^2. \end{aligned}$$

$\rho \leq 0$ is sufficient to ensure that $E(x_2|G_4) \geq 0$, $E(w_2|G_4) \geq 0$, and $E(w_2|G_4) \geq E(w_2|streaming, random\ occupational\ assignment)$, where $E(w_2|streaming, random\ occupational\ assignment) = p_2 + \mu_2 + \sigma_1^{-1} F(k/\sigma_1)(1 - v)\theta$.

(A5) Stream 1 Academic Skills

$$E(x_1|x_1 \geq k) = \frac{\sigma_1^2 f(k/\sigma_1)}{\sigma_1 - F(k/\sigma_1)}$$

$$Var(x_1|x_1 \geq k) = \sigma_1^2 + \frac{\sigma_1^2 k f(k/\sigma_1)}{\sigma_1 - F(k/\sigma_1)} - \left(\frac{\sigma_1^2 f(k/\sigma_1)}{\sigma_1 - F(k/\sigma_1)}\right)^2$$

$E(x_1) = 0$, thus, $E(x_1|x_1 \geq k) \geq E(x_1)$ $\forall$ $k, v, \theta, \rho, p_i, \sigma_i$, and μ_i for $i = 1, 2$. Further, $Var(x_1) = \sigma_1^2$, hence, $Var(x_1|x_1 \geq k) \leq Var(x_1)$ because $k \leq \frac{\sigma_1^2 f(k/\sigma_1)}{F(k/\sigma_1)}$.

(A6) Stream 2 Vocational Skills

$$E(x_2|x_1 < k) = -\frac{\rho\sigma_1\sigma_2 f(k/\sigma_1)}{F(k/\sigma_1)}$$

$$Var(x_2|x_1 < k) = \sigma_2^2 - \frac{\rho^2\sigma_2^2 k f(k/\sigma_1)}{F(k/\sigma_1)} - \left(\frac{\rho\sigma_1\sigma_2 f(k/\sigma_1)}{F(k/\sigma_1)}\right)^2$$

As $E(x_2) = 0$, $E(x_2|x_1 < k) \geq E(x_2)$ iff $\rho \leq 0$. $Var(x_2) = \sigma_2^2$, hence, $Var(x_2|x_1 < k) \leq Var(x_2)$ iff $k \geq \frac{-\sigma_1^2 f(k/\sigma_1)}{F(k/\sigma_1)}$.

Appendix B
Comparative Statics for Selected Conditional Moments

$$\frac{\partial E(w_1|G_1)}{\partial k} = \Pi_{11}^{-1}\sigma_1^{-1} f(k/\sigma_1)\Big\{F(A_1)E(x_1|G_1) - kF(A_1) + \frac{\sigma_1^2 c}{\sigma_2} f(A_1)\Big\}$$

$$\frac{\partial E(w_1|G_2)}{\partial k} = -\Pi_{21}^{-1}\sigma_1^{-1} f(k/\sigma_1)\Big\{F(A_2)E(x_1|G_2) - kF(A_2) + \frac{\sigma_1^2 c}{\sigma_2} f(A_2)\Big\}$$

$$\frac{\partial E(w_2|G_3)}{\partial k} = \Pi_{12}^{-1}\sigma_1^{-1} f(k/\sigma_1)\Big\{[1 - F(A_1)]E(x_2|G_3) - \rho\sigma_1^{-1}\sigma_2 k[1 - F(A_1)] - [\sigma_2(1-\rho^2) + \sigma_1\rho]cf(A_1)$$

$$\frac{\partial E(w_2|G_4)}{\partial k} = -\Pi_{22}^{-1}\sigma_1^{-1} f(k/\sigma_1)\Big\{[1 - F(A_2)]E(x_2|G_4) - \rho\sigma_1^{-1}\sigma_2 k[1 - F(A_2)]$$

Appendix C
Data and Variable Definitions

All wage data is 1984 *Wave II: German Panel Survey* data from the Luxembourg Income Survey. This survey includes 5174 households and is weighted to be representative at the individual level. My sub–sample includes full–time, civilian, married, non-disabled, male workers aged 35 to 44 who report some form of occupational training. This sub–sample contains 429 observations.

Individuals are assigned either the academic or vocational stream. Stream placement is determined by the type of occupational training claimed. To facilitate this I further restrict the sample to individuals who attended high school.

(C1) Vocational Stream

Individuals who recieved one of the following types of occupational training:
general apprenticeship
trade, technical or agricultural apprenticeship

commercial or other apprenticeship
special vocational school
special public health school
senior craftsman or technical training

(C2) Academic Stream
Individuals who recieved one of the following types of occupational training:
public service training
college or engineering
university training

The 1984 *Wave II: German Panel Survey* provides relatively detailed information about worker type. Blue and white collar occuaptions are clearly defined. Worker status is divided into thirty–three categories.

(C3) Blue Collar Occupations
unskilled public worker
semi–skilled public worker
skilled public craftsman
public service foreman
public building foreman
unskilled private worker
semi–skilled private worker
skilled private craftsman
private sector foreman
private building foreman

(C4) White Collar Occupations
white–collar public sector foreman
white–collar public sector worker
qualified white collar public sector worker
highly qualified white collar public sector worker
white collar public sector manager
white–collar private sector foreman
white–collar private sector worker
qualified white collar private sector worker
highly qualified white collar private sector worker
white collar private sector manager
low level public service
high level public service
high public official
academic professions

(C5) Excluded Occupations
non–worker
apprentice
volunteer or trainee
independent farmers
self–employed
family member assistance