Education System Permeability

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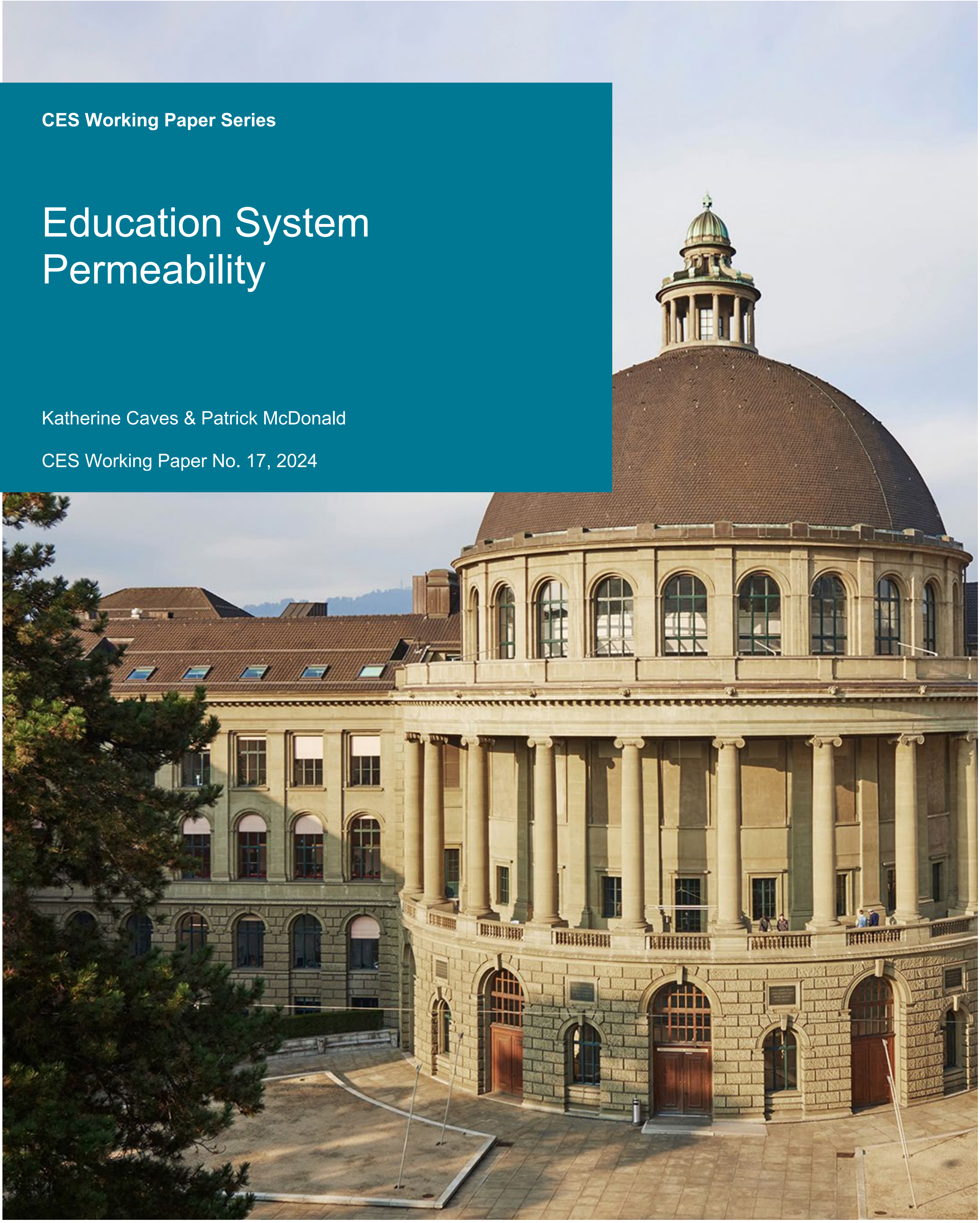

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Education System Permeability

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Abstract

This paper proposes a model of returns to education based on the permeability of the education system. We define permeability as the availability of different program types up to the highest education levels and the ability to transition between programs (Caves et al., 2023). We develop six permeability models that reflect variation in the availability of programs and transitions. Building on Heckman et al. (2006)'s work on returns to education by skill type, we formulate a model of returns to education in each type based on skill types and schooling type. We then specify this model for each permeability type. We use a Monte Carlo simulation to demonstrate how the model performs for each permeability type as we progressively relax assumptions. We find that education system permeability is necessary but not sufficient for maximizing individual returns to education, especially for individuals whose latent skill profiles are more aligned with the non-dominant type of education. Population skills are also higher in higher-permeability systems. We further find that high overall ability cannot compensate for the “wrong” skill type in a low-permeability system. After considering the literature, we show that permeability is also necessary for the accurate comparison of program types and that permeability increases the attractiveness of non-dominant programs by increasing further education opportunities. Program quality is crucial since permeability does not yield effects on its own, but a high-quality program cannot overcome the limitations of a low-permeability system.

JEL Codes

I26, I24, J24

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Education System Permeability

Introduction

Over the last few centuries, schooling has gone from the province of the elites to a fundamental and universal right. Even as access to primary, secondary, and even tertiary levels of education have expanded, issues of equity and efficiency continue to challenge policymakers, practitioners, and students. Globally, although individual factors like gender and wealth affect learning outcomes, "systems-related" factors remain the dominant source of inequality in learning achievement across countries (Crouch et al., 2021). However, those system-level factors can be difficult to conceptualize, making research and potential intervention complex.

This paper proposes a model of returns to education based on the permeability of the education system. We define permeability as the availability of different program types up to the highest education levels and the ability to transition between programs (Caves et al., 2023). We develop six permeability models that reflect variation in the availability of programs and transitions. Building on Heckman et al. (2006)'s work on returns to education by skill type, we formulate a model of returns to education in each type based on skill types and schooling type. We then specify this model for each permeability type. We use a Monte Carlo simulation to demonstrate how the model performs for each permeability type as we progressively relax assumptions. We discuss how our findings relate to the existing empirical literature.

We find that education system permeability is necessary but not sufficient for maximizing individual returns to education, especially for individuals whose latent skill profiles are more aligned with the non-dominant type of education. Population skills are also higher in higher-permeability systems. We further find that high overall ability cannot compensate for the "wrong" skill type in a low-permeability system. After considering the literature, we show that permeability is also necessary for the accurate comparison of program types and that permeability increases the attractiveness of non-dominant programs by increasing further education opportunities. Program quality is crucial since permeability does not yield effects on its own.

Review of the literature on permeability

Probably the simplest way to talk about an education system is the programs and pathways it offers. In this context, the word “permeability” is often used to describe education systems with a wide variety of options. In popular usage, it is associated with education systems that have “no dead ends,” or programs that do not lead to potential higher education options. The literature on permeability in education systems is most often focused on transitions between levels—for example from secondary to tertiary education (e.g., Stephan & Rosenbaum, 2012)—or between types of education—for example academic and vocational education (e.g. Hartmann et al., 2009). However, a clear definition of permeability is missing in the academic literature.

Education system permeability has to date mostly been the topic of applied research (see, for instance, Caves et al. 2023; Graf et al. 2021, Cedefop 2012). While these publications deal with the institutional contexts of (a lack of) permeability, they do not grapple with a definition of permeability, with the exception of Caves et al. (2023), who propose a permeability framework based on the two axes of access – the pathways available to move from one program to another – and opportunity, or the availability of programs within different educational streams and on different educational levels. While this definition is practically useful, it lacks theoretical underpinning. Moreover, studies of permeability, applied or otherwise, have thus far often focused on German-speaking Europe (see also Wolter 2012, Hartmann et al., 2009) – one example from the U.S., Stephan and Rosenbaum (2012) does focus on permeability but only within academic pathways.

When empirical academic literature covers permeability, it often does so from the angle of outcomes of systems that offer multiple pathways, without focusing on permeability explicitly. A developed strand of this research comes from Switzerland, where a series of articles presents the economic benefits of multiple educational pathways. Tuor and Backes-Gellner (2010) show that the Internal Rate of Return to education is highest amongst students who begin in an academic program and finish in a vocational one, while all other possible pathways beyond compulsory education also show positive rates of return. Balestra and Backes-Gellner (2017) demonstrate that differing pathway options are critical for economic returns at the lower end of the skills distribution, reinforcing the notion that providing education options beyond academic is especially important for ensuring equity of outcomes. Finally, Backes-Gellner and Lehnert (2021) show that adding vocational options and pathways between academic and vocational education fosters economic innovation and overall growth, adding an aggregate perspective to the more individual-level findings of other work on the topic.

A second theme related to, but not directly exploring, permeability, is how to ensure non-academic programs are viable alternatives to academic ones. For example, Meer (2007) shows evidence that—when controlling for academic ability and other factors, youth choosing vocational secondary in the US would be no better off had they chosen an academic path. Non-academic pathways typically suffer from low social status (Cedefop 2014), but two articles from Bolli and Rageth (2016) and Bolli et al. (2018) show that in Switzerland, an education system that offers a multitude of programs and pathways, this is not the case. Indeed, as measured by PISA test scores, the social status of vocational programs at the upper-secondary level is only marginally lower than that of academic programs. Importantly, this research is not able to causally identify the basis of this more equal social status, though it does suggest that education system permeability may play a role. Moreover, the counterfactual – that a lack of permeability may explain a lower social status, is difficult to study.

A model of returns to education based on permeability

A large economic literature begun by Becker (1962) is concerned with skills, education, and labor market returns. In this literature, it is accepted that individuals earn heterogeneous returns to schooling, which are largely but not completely explained by ability (Heckman et al., 2018). Individuals begin schooling with some amount of latent ability, and education and training "activate" these skills, making them measurable and relevant for wages. Individuals' labor market returns are, therefore, a function of latent skills and years of education, along with personal and other factors (Mincer, 1974).

Returns to education by skill type

Beginning with human capital theory, the economic literature differentiates different types of skills, arguing that skill type modifies the relationship between education and skills activation and/or activated skills and labor market returns (Becker, 1962). Becker differentiates between general and specific skills, where general skills are useful across occupations and firms and specific skills are primarily useful in one occupation or firm. Lazear (2009), however, argues that all skills are general and individuals' unique bundles of skills are specific to their occupations or firms. Heckman et al. (2006) differentiate cognitive and non-cognitive skills, arguing that noncognitive skills influence educational choices and wages (given educational choices), and latent skills of both types affect labor market outcomes. Autor et al (2003) and Deming et al. (2016) make similar distinctions, but refer to technical and social skills, and cognitive and social skills, respectively.

Heckman et al. (2006) show that both latent cognitive and noncognitive skills respond to education, and shape both educational choices and later-life outcomes like health and the labor market (Heckman et al., 2018). We build on Heckman et al.'s (2006) model of returns to schooling based on cognitive and non-cognitive latent skills, shown in (1). In Heckman's equation, I_s represents the net benefits of each schooling level s among $\bar{S}$ possibilities (S = {1, …$\bar{S}$}). X_i is a vector of observed individual characteristics and β_1 is the effect of those individual characteristics on skill activation. f^C and f^N are individuals' latent cognitive and non-cognitive abilities, respectively. α_s^C and α_s^N are factor loadings for cognitive and non-cognitive latent abilities, respectively—these show how much each latent ability type responds to schooling. e_s is an error term.

$$I_s = \beta_s X_s + \alpha_s^C f^C + \alpha_s^N f^N + e_s \text{ for } s = 1, \ \dots, \bar{S} \qquad (1)$$

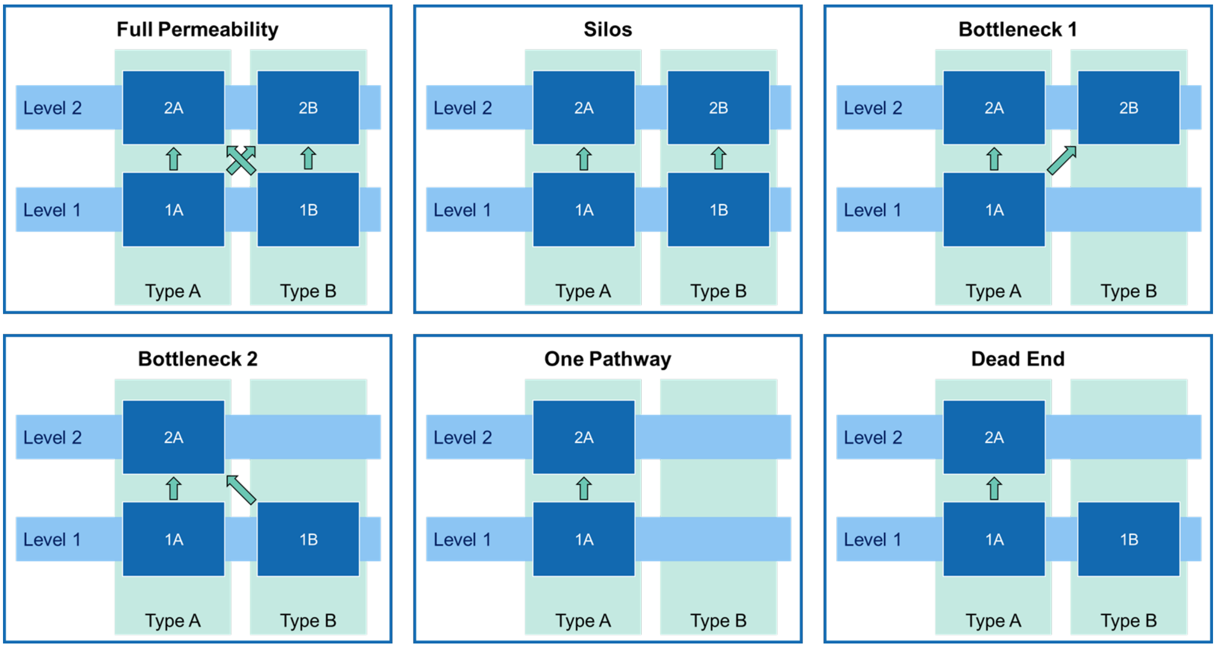
We follow Heckman et al. (2006) by postulating two factors that represent latent skills. We do not, however, assume that A and B represent any particular type of skills. We refer to these latent skill types simply as A and B. f^A and f^B represent latent skill A and skill B, respectively. Like Heckman and coauthors, we assume that skills A and B are equally valued on the labor market. Individuals have varying levels of each latent skill type resulting from some combination of genetics, environment, and other factors. Again following Heckman et al. (2006), we begin with the assumption that latent skill types are independent, and we assume that individual latent skills are fixed by the time individuals make schooling choices.

Different types of schooling

We add to the model by postulating two types of schooling, also A and B. Each latent skill type is more responsive to the matched type of schooling and less responsive to the non-matching type of schooling. Education-focused literature finds comparative advantages for different types of education on the development of various skill types. For example, Raelin (1997) differentiates theoretical and practical learning in one dimension, and explicit and tacit knowledge in a second dimension. The importance of each learning type varies depending on the skill being learned, meaning that different learning environments have comparative advantages for different skills. Goldin (2001), for instance, applies Becker's skills typology and argues that formal, school-based education has the strongest effect on general skills, while workplace-based education is most effective for specific skills.

However, different types of education are not always available to individuals. To formally consider how an education system's offering of different types of skills and education relate to individual outcomes, we need to model what programs and transitions are available to individuals. We simplify down to two post-compulsory levels of schooling, which we call 1 and 2. We wish to clarify that level 1 does not refer to primary education (e.g. ISCED level 1). Instead, it 1 is analogous to upper secondary education (ISCED level 3, possibly 4 depending on context) and level 2 is analogous to tertiary or post-secondary education (ISCED level 5+, possibly including 4 depending on context). An education program occupies one level and type in the education system, so this yields four potential programs: 1A and 1B at the lower level of schooling, and 2A and 2B at the higher level of post-compulsory schooling.

Figure 1: Permeability models



Notes: Permeability models are adapted from those used by Caves et al. (2023). Models represent a highly simplified and partial view of an education system. Levels indicate post-compulsory levels, e.g. (upper) secondary and tertiary or approximately ISCED levels 3-4 and 4-8 depending on context. Types are intentionally unspecified.

We draw on Caves et al. (2023), defining education system permeability in terms of programs and transitions. A model is permeable in terms of programs when there are programs in both types (A and B) at both levels (1 and 2) such that all four potential programs are available. A model is permeable in terms of transitions when students can move between levels and types of education. In our simplified models, we reduce the transitions to only upward and upward diagonal transitions, ignoring horizontal transitions. The purpose of this simplification is to generate a small set of types that can be useful for illustrative modeling. This generates the six extremely simplified permeability models in Figure 1.

An individual's endowment of latent skill type A is given by f_i^A and of skill type B is given by f_i^B. With two types of latent skills and two types and levels of education, an individual's activated skills after education Y_i—observable through outcomes like skills, employment, wages, and others—is a function of latent skills by type, schooling by level L and type—captured by γ, a dummy variable that takes the value 1 when the individual is in type A education—and observable variables X_i. Skills after education are given by the following specification (1):

$$Y_i = \beta_i X_i + \sum_{L=(1,2)} [\gamma(\alpha_L\, f_i^A + \omega_L\, f_i^B) + (1-\gamma)(\omega_L\, f_i^A + \alpha_L\, f_i^B)] + \varepsilon_i \tag{2}$$

The effect of schooling on latent skills differs depending on whether the program type matches the latent skill type. The effect of schooling in level L for matching programs is shown by α_L , and the effect of schooling in level L for mismatched programs is shown by ω_L . Depending on whether they are in a type A or type B education program, individuals can have either matched schooling effects α_L on their latent type A skills f_i^A and mismatched schooling effects ω_L on their latent type B skills f_i^Bor the inverse. ε_i is an idiosyncratic error term. This model applies to education levels 1 and 2.

In sum, there are four main parameters affecting individuals' activated skills after education Y_i in (2). First are individual factors $\beta_i X_i$ beyond an individual's latent skills and education. Second is γ, which captures the type of education program the individual pursues. Third is the effectiveness α of education programs for the matched latent skills. Fourth is the effectiveness ω of education programs for the mismatched latent skills. We expect that education is more effective for matched latent skills and less effective for mismatched latent skills ($\alpha > \omega$), but not completely ineffective for mismatched latent skills ($\omega \neq 0$).

Modeling non-completion

A fifth parameter that affects individuals' activated skills after education Y_i is their access to years of education (Mincer, 1974). Therefore, (2) models the levels of education separately as $Y_i(L1)$ and $Y_i(L2)$, then states that Y_i is the sum of $Y_i(L1)$ and $Y_i(L2)$ given that $Y_i(L1)$ is greater than the requirement R. We capture whether $Y_i(L1)$ is greater than R in a dummy, D, which takes the value of 1 if the requirement is met and 0 otherwise. Therefore, the two levels of education are not completely independent—access to the second level of education is dependent on latent skills activation in the first level.

$$\begin{gathered} Y_i(L1) = \beta_i X_i + [\gamma(\alpha_1\, f_i^A + \omega_1\, f_i^B) + (1-\gamma)\,(\omega_1\, f_i^A + \alpha_1\, f_i^B)] + \varepsilon_i \\ D = 1\; if\; Y_i(L1) > R, 0\; otherwise \\ Y_i(L2) = \beta_i X_i + [\gamma(\alpha_2\, f_i^A + \omega_2\, f_i^B)\; or\; (1-\gamma)(\omega_2\, f_i^A + \alpha_2\, f_i^B)] + \varepsilon_i \\ Y_i = Y_i(L1) + [Y_i(L2) * D] \end{gathered} \tag{3}$$

Modeling permeability

Finally, we add a sixth parameter showing how the ability of individuals to access the education programs that match their latent skills varies by permeability model. We model access to programs in each permeability model by modifying the available programs. We discuss how assumptions about individuals' information about program matching affects Y_i.

Equations (2) and (3) show systems where individuals have access to both types of education at both levels. These align with permeability models *Full Permeability* and *Silos*, where the availability of education programs is the same. With the assumption of perfect information about program matching, the two permeability models are indistinguishable.

When we relax the assumption that individuals have perfect information about which program matches their latent skills, a difference emerges between *Full Permeability* and *Silos*. With imperfect information, individuals may choose the mismatched program type and their skill activation through education Y_i will be lower because of the mismatch. In *Full Permeability*, individuals may switch to the matching program at level 2, reducing the impact of the mismatch. In *Silos*, individuals cannot change their education type as they progress to the second level, so they must continue to invest in the mismatched education type and will have lower skill activation due to the mismatch. Therefore we expect lower Y_i on average in *Full Permeability* and *Silos* with imperfect information, and a stronger effect in *Silos*.

In the *Bottleneck 1* permeability model, there is one education type available at level 1 (type A) and both types are available at level 2. Equation (4) models this permeability model by dropping education program B1. All individuals for whom f_i^B is greater than f_i^A will have lower skill activation due to the mismatch at level 1. This lowers Y_i directly for type-B dominant individuals. It also lowers Y_i indirectly by making advancement to Level 2 less likely for individuals for whom f_i^B is greater than f_i^A.

If we relax the assumption of perfect information about matching, there is no effect at level 1 due to the lack of options. We expect lower $Y_i(L2)$ on average due to increased mismatch, but there is no additional bias towards either latent skill type.

$$
\begin{gathered}
Y_i(L1) = \beta_i X_i + \alpha_1\, f_i^A + \omega_1\, f_i^B + \varepsilon_i \\
D = 1\ if\ Y_i(L1) > R, 0\ otherwise \\
Y_i(L2) = \beta_i X_i + \left[\gamma(\alpha_2\, f_i^A + \omega_2\, f_i^B\right) + (1-\gamma)(\omega_2\, f_i^A + \alpha_2\, f_i^B)] + \varepsilon_i \\
Y_i = Y_i(L1) + [Y_i(L2) * D]
\end{gathered}
$$

(4)

In the *Bottleneck 2* and *Dead End* permeability models, both education types exist at level 1 but only type A exists at level 2. However, in *Dead End,* individuals who start in type B education cannot progress to tertiary education in type A. Equation (4) models the *Bottleneck 2* permeability model. Although $Y_i(L1)$ remains unchanged, Y_i is lower for all individuals with latent type B skills f_i^B due to mismatch at level 2. If we relax the assumption of perfect information, we see lower Y_i on average driven by lower $Y_i(L1)$. This effect is stronger for individuals for whom f_i^B is greater than f_i^A.

$$
\begin{gathered}
Y_i(L1) = \beta_i X_i + [\gamma(\alpha_1\, f_i^A + \omega_1\, f_i^B) + (1-\gamma)(\omega_1\, f_i^A + \alpha_1\, f_i^B)] + \varepsilon_i \\
D = 1\ if\ Y_i(L1) > R, 0\ otherwise \\
Y_i(L2) = \beta_i X_i + \alpha_2\, f_i^A + \omega_2\, f_i^B + \varepsilon_i \\
Y_i = Y_i(L1) + [Y_i(L2) * D]
\end{gathered}
$$

(5)

The *Dead End* permeability model, shown in (5), has the same program availability as *Bottleneck 2* in (4), but the conditions to enter level 2 are different. For those who enter from type A in level 1, the conditions are the same. For those who enter level 2 from type B in level 1, there is no education program available so $Y_i(L2)$ is zero. This directly lowers Y_i for all individuals for whom f_i^B is greater than f_i^A because they cannot access the level 2 program matched to their latent skills.

When we relax the assumption of perfect information about program matching in the *Dead End* pathway in (6), we expect to see lower Y_i on average. Individuals with higher f_i^A in matched programs remain the same and have the same probability of accessing level 2 programs. Individuals with higher f_i^B in matched programs still cannot progress to level 2 education. Individuals with higher f_i^A in mismatched programs at level 1 now cannot progress to level 2. For Individuals with higher f_i^B in mismatched programs, there is an opportunity to progress to level 2 education but, because of the mismatch, their level 1 program might not yield sufficient $Y_i(L1)$ for progression so we expect a lower overall rate of progression from level 1 to level 2.

$$Y_i(L1) = \beta_i X_i + [\gamma(\alpha_1\ f_i^A + \omega_1\ f_i^B) + (1-\gamma)(\omega_1\ f_i^A + \alpha_1\ f_i^B)] +\ \varepsilon_i$$
$$D = 1\ if\ Y_i(L1) > R, 0\ otherwise$$
For L1 in type A: $Y_i(L2|Y_i(L1) > R) = \beta_i X_i + \alpha_2\ f_i^A + \omega_2\ f_i^B + \varepsilon_i$

For L1 in type B: $Y_i(L2|Y_i(L1) > R) = 0$
$$Y_i = Y_i(L1) + [Y_i(L2) * D]$$

(6)

Finally, (7) models the *One Pathway* permeability model. In this type, only type A education is available at both levels. All individuals for whom f_i^B is greater than f_i^A will have lower skill activation due to the mismatch at both levels, lowering Y_i directly. Y_i is also indirectly lowered because it is more difficult for individuals for whom f_i^B is greater than f_i^A to advance to Level 2. There is no effect of imperfect information because there are no choices.

$$Y_i(L1) = \beta_i X_i + \alpha_1\ f_i^A + \omega_1\ f_i^B +\ \varepsilon_i$$
$$D = 1\ if\ Y_i(L1) > R, 0\ otherwise$$
$$Y_i(L2) = \beta_i X_i + \alpha_2\ f_i^A + \omega_2\ f_i^B + \varepsilon_i$$
$$Y_i = Y_i(L1) + [Y_i(L2) * D]$$

(7)

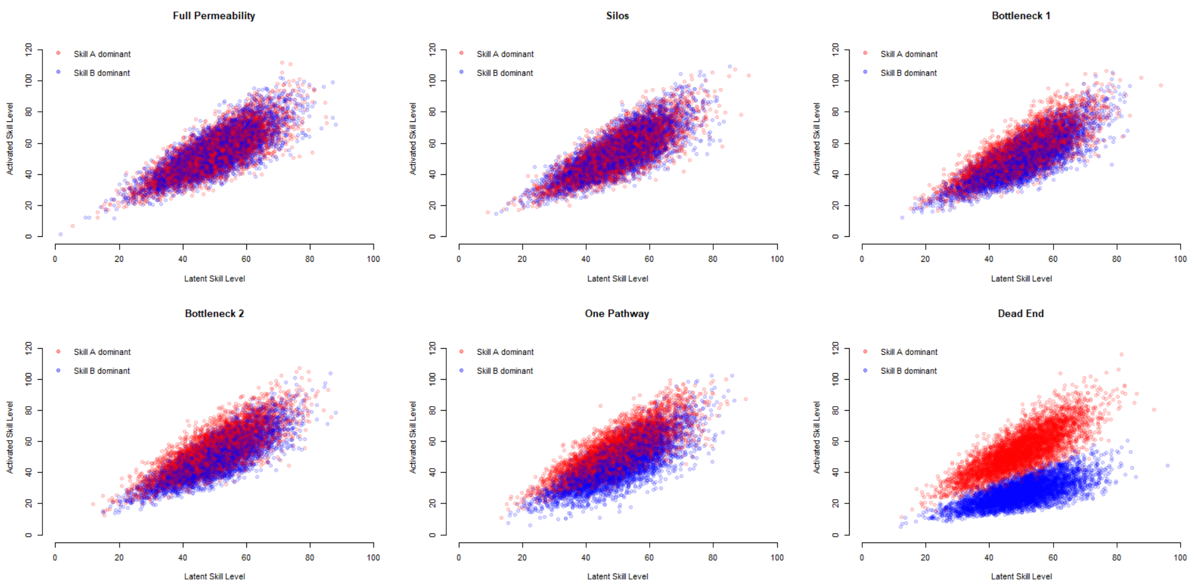
Demonstration

For illustrative purposes, we apply the model defined above in a Monte Carlo simulation. We begin in a perfect world, then systematically add complexity and relax assumptions. In a population of 10,000 students, each individual is randomly assigned a latent skills endowment of type A f_i^A and type B f_i^B along a normal distribution between 0 and 50. Total latent skill endowments therefore range between 0-100, with a mean and median around 50. We simulate sending our population of individuals through each education system permeability model using the models articulated in the previous section.

Like Heckman, we assume that latent skills are independent and that individuals are aware of their latent skills composition. We further assume that education is more effective for the matching latent skill type than it is for the non-matching type. Specifically, we assume that the effectiveness α of an education program for the matching latent skill type varies randomly between 0.5-1 and its effectiveness ω for non-matching latent skill type varies randomly between 0-0.5. Therefore, a matching program activates the majority of matching skills and at least some non-matching skills. The effectiveness of each education program is independent, so an individual can have different skill activation through their secondary and tertiary programs even within types.

We begin in a perfect world. In this model, we assume perfect information such that individuals are always in education programs that match their dominant latent skill type. We further assume that every individual completes both levels of education. Figure 1 plots individuals' activated skills Y_i against their total latent skill levels $(f_i^A + f_i^B)$ under the conditions of the perfect world. We show results for each permeability model, starting with full permeability and progressing to the least permeable models. Individuals are color coded according to their dominant skills, with red dots having more type A than type B skills and blue dots having more type B than type A skills, regardless of overall level.

Figure 2: Individual skill activation by permeability model, perfect world



Note: red dots are individuals dominant in latent skill A, blue dots are individuals dominant in latent skill B. The x-axis shows total latent skill level and the y-axis shows total activated skill level after secondary and tertiary education (if available). This figure shows results for a perfect world where individuals have perfect information to choose the education program that matches their dominant skill type and everyone completes secondary and tertiary education (if available).

In Figure 2, it is immediately clear that—even in a perfect world—education system permeability has an impact on individuals' skills activation through education. In the most permeable systems—*Full Permeability* and *Silos* are indistinguishable due to the assumption of perfect information—there is a consistent correlation between latent and activated skills, with no segregation by dominant latent skill type. As permeability decreases, the influence of latent skill type increases. In the *Bottleneck 1, Bottleneck 2,* and *One Pathway* models, only the individuals with the highest total latent ability can attain high skill activation regardless of latent skill type. In the *Dead End* model, even the individuals with the highest total latent skills are unable to overcome the restrictions imposed by the education system.

We systematically relax assumptions, implementing simulations for all permeability types across a range of varying parameters. Specifically, we do not modify the allocation of latent skills to individuals or the size of the population, but we relax our assumptions about perfect attainment, perfect information, and non-discrimination. Table 1 summarizes the parameters for each simulation. Plots like Figure 1 are available in the Appendix 1 for each simulation.

Table 1: Summary of simulation parameters and assumptions

Simulation	1	2	3	4	5
Parameters	Perfect world	Allow tertiary non-completion	Allow imperfect information	Information worse for earlier choice	Allow discrimination
Type A latent skills f_i^A	Normally distributed 0-50	Normally distributed 0-50	Normally distributed 0-50	Normally distributed 0-50	Normally distributed 0-50
Type A latent skills f_i^B	Normally distributed 0-50	Normally distributed 0-50	Normally distributed 0-50	Normally distributed 0-50	Normally distributed 0-50
N	10,000	10,000	10,000	10,000	10,000 (**5,000 each group**)
Activated skills required for tertiary (*R*)	NA	**25**	25	25	In-group: 25 **Out-group: 35**
p(matched program) at level 1 (γ)	1	1	**0.75**	**0.625**	In-group: 0.625 **Out-group: 0.5**
p(matched program) at level 2 (γ)	1	1	**0.75**	0.75	In-group: 0.75 **Out-group: 0.625**
Matched program effectiveness (α)	Random 0.5-1.0	Random 0.5-1.0	Random 0.5-1.0	Random 0.5-1.0	In-group: 0.5-1.0 **Out-group: 0.4-0.9**
Mismatched program effectiveness (ω)	Random 0.0-0.5	Random 0.0-0.5	Random 0.0-0.5	Random 0.0-0.5	In-group: 0.0-0.5 **Out-group: 0.0-0.4**

Note: Table summarizes simulations with varying parameters in a world with two education levels (1 and 2) and two types of education (A and B). Each type of education is matched to one of two latent skill types (A and B). We assume that education programs (in a given level and type) activate matched latent skills more than mismatched latent skills. Individuals have an endowment of both latent skill types. Latent skill endowments are independent by type, as is the effectiveness of matched and mismatched education. Both skill types are equally valued on the labor market. Latent skills are fixed and known by the time individuals make schooling choices. In the latter simulations, individuals have imperfect information about whether education programs match their latent skills.

The first assumption we relax is that every individual completes both levels of education. Individuals' skill levels after secondary education are the product of their latent skills of both types and the effectiveness of the program they attended for each latent skill type. Activated skill levels after secondary education can theoretically range from 0-75. Because mean latent skills are 50 and mean program effectiveness is around 0.75, the mean activated skill level after secondary education is approximately 37.5. Therefore, to relax the assumption that every individual successfully completes tertiary education, we allow only individuals with an activated skill level higher than 25 after secondary education to complete tertiary education.

The second assumption we relax is that individuals have perfect information about which program type matches their latent skills. Following our assumptions, individuals are aware of their own latent skills. However, they may not have perfect information about which education type is the best match. Therefore, in the third simulation, we give individuals a 75% probability of choosing the program that matches their dominant latent skill type. Again these choices are independent at each education level when the permeability model allows.

The third assumption we relax is that individuals' information about education program matching is stable over time. Instead, individuals may learn more about education options from experience in the system. Therefore, we lower the probability of choosing the program that matches their dominant latent skills for level-one education only, such that at the first level the probability of matched education is 62.5% and at level two it remains 75%. This adjustment reflects the idea that educational experience increases knowledge about program content.

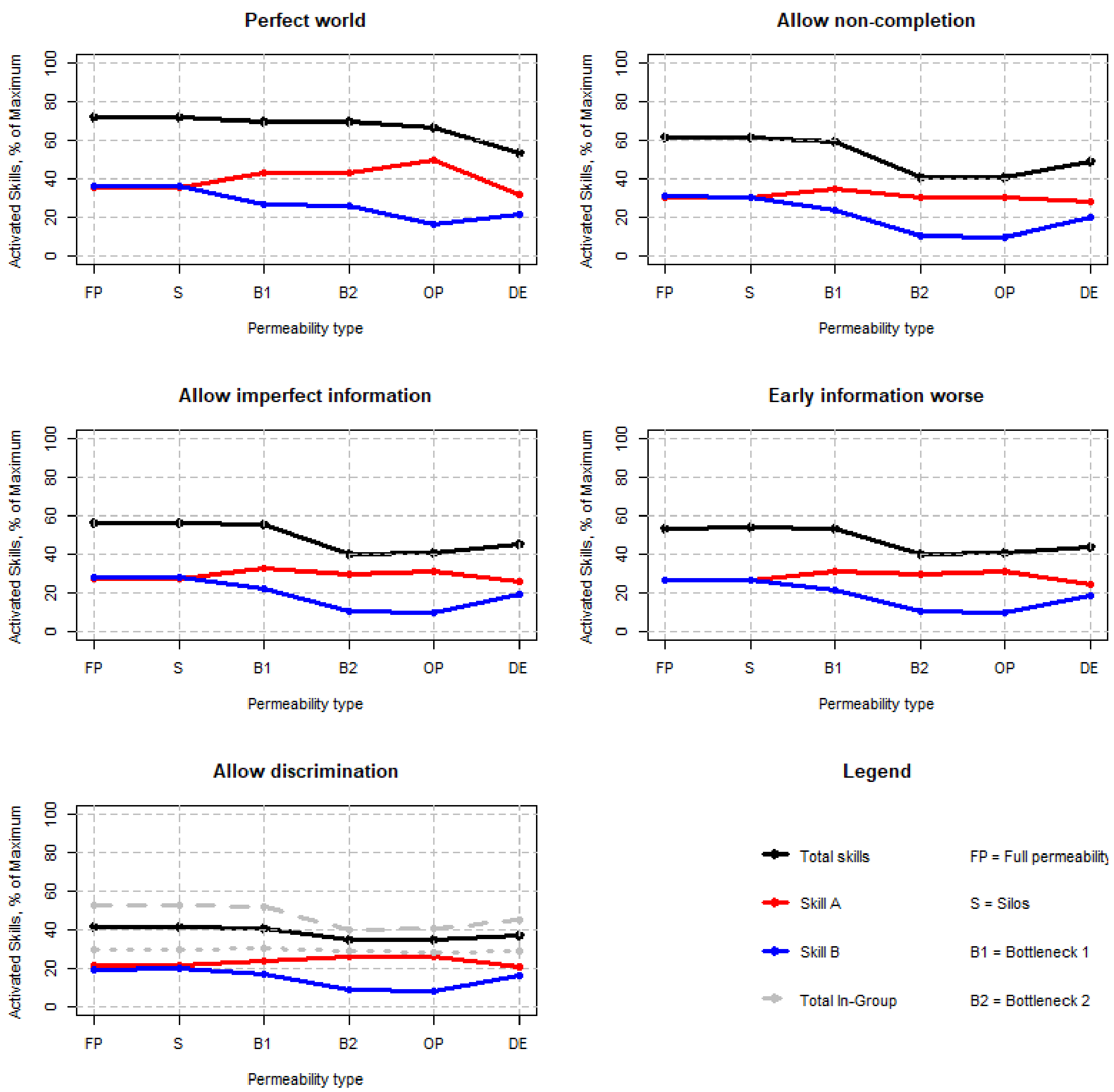
Finally, we relax the assumption that all individuals are treated equally. In the final simulation, we allocate half of the population randomly to an unspecified "out-group." For members of the out-group, the requirements for completing level two education are higher (35 points instead of 25), the probability of being in the matched education program at both levels is lower (0.5 and 0.625 respectively, instead of 0.625 and 0.75 respectively), and education is slightly less effective (0.4-0.9 for matched latent skill/education types instead of 0.5-1, and 0-0.4 for mismatched latent skills/education types instead of 0-0.5). We elaborate on these parameters in the discussion section.

These parameters—higher admissions standards, higher risk of mismatched programs, and decreased education effectiveness—all reflect conservative versions of phenomena that have been observed for various out-groups based on gender, race, religion, migration status, and other factors in empirical research. The literatures on affirmative action and standardized testing biases both highlight how admission to higher education is more difficult for students in certain groups (E.g. Harrison et al., 2006; Rosinger et al., 2021). Studies on tracking and streaming highlight the disproportionate effects of low-quality programs and discriminatory selection processes on disadvantaged groups (e.g. Hanushek & Wößmann, 2006; Oakes, 2005). Similarly, research on teacher biases and their impact on student placements highlight the risk of mismatched placement for students facing discrimination e.g. Glock et al., 2015; Podell & Soodak, 1993). For educational effectiveness, evidence related to education quality and resource disparities shows that students in some areas or schools may have lower quality education in a way that reinforces systemic inequity (e.g. Darling-Hammond, 2013). Finally, research on culturally responsive teaching shows how classroom environments and teaching styles can include or exclude students, affecting their educational outcomes (e.g. Ladson-Billings, 1995).

Cohort-level results for skill activation by type

One way to evaluate the success of different permeability models is to consider the total activated skills within a cohort once they have completed education. Figure 3 shows the results, with skills being reported as a percentage of total potential for activated skills after both education levels. We observe lower total skill activation with less permeable models, possibly leading to vertical skills mismatch. This decrease comes from a decrease in B-type skills, possibly leading to horizontal skills mismatch.

Figure 3: Cohort-level skill activation by simulation and permeability type



Note: the black lines show the total skills activated in a simulation and permeability type as a percentage of the total possible activated skills. The red line shows the proportion of A skills in the overall activated skills, the blue line shows the proportion of B skills. The x axis shows different permeability types from the most to least permeable. Each individual graph represents a different simulation based on the varying parameters shown in table 1.

Two things become immediately clear related to total skills (shown in black): first, the total amount of skills decreases as systems become less permeable, and second, that each relaxation of assumptions built into the simulation models also results in a reduction of the total skills available. In the best simulation—*Full Permeability* in the "perfect world", approximately 80% of latent skills are activated. In the worst—*One Pathway* in the simulation allowing discrimination, this drops to 40%, and only 30% for the out-group suffering from systemic discrimination.

The reduction in total skills as systems become less permeable does not look large at first glance, especially between the *Full Permeability, Silos*, and *Bottleneck 1* models, where the differences in skills activation are quite small. However, these relatively small overall differences mask large changes in the distribution of skills types. While in the *Full Permeability* and *Silos* models, skill type A and B account for the same proportion of the activated skills, a large gap opens in all other simulations, reaching its largest in the *One Pathway* model, where the concentration of activated A-type skills is approximately twice that of B-type skills. Given that we assume the labor market demands the most skills possible and an equal mix of A and B skills, only the *Full Permeability* and *Silos* types deliver to an acceptable extent on both.

A final observation may be made for the simulations where systemic discrimination is present. In this simulation, as expected, we see lower total activated skills for the out-group over the in-group. Because the in-group does not benefit, the direct effect of this is much lower total skills activation. In terms of total skills available on the labor market and skills balance, systemic discrimination has negative consequences for all, not only those directly affected by it.

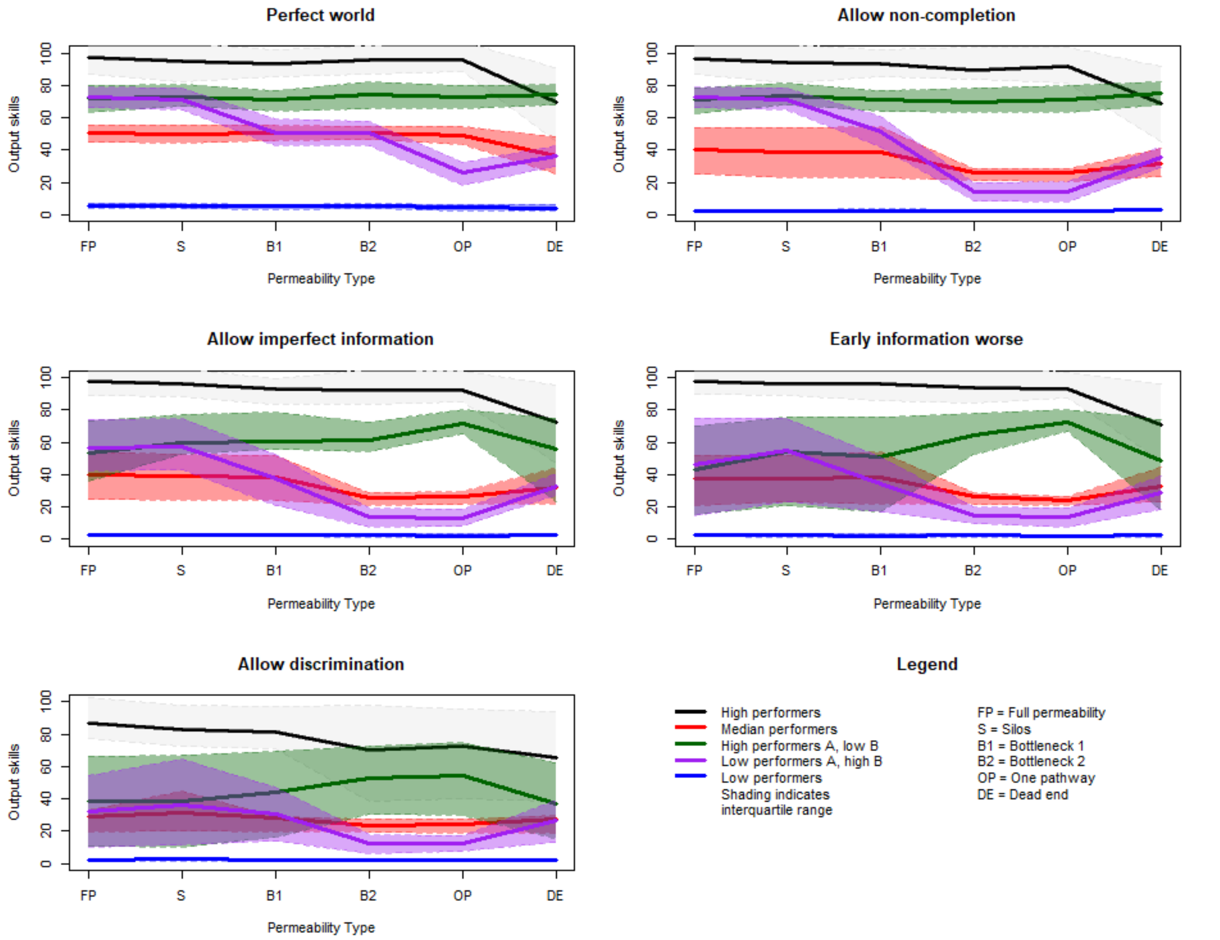
Results for individuals by latent skill profile

Previous results have referred to the overall availability of skills based on permeability type and simulation assumptions. Here, we explore the outcomes for different student profiles. To do so, we create five ideal-types of students: One high achiever type, whose latent skills are at least one standard deviation above the mean for both A and B, one “average” type, between one standard deviation from the mean in either direction for both, one low achiever type, one standard deviation below the mean for both, and a “High A, Low B” type (more than one standard deviation above the mean in A, one below in B) and a “Low A, High B” type (more than one standard deviation below the mean in A, one above in B). It is important to note that these groups are not intended to capture the full cohort, but rather to illustrate potential outcomes based on a number of typical profiles.

The graphs in Figure 4 illustrate the total activated skills each of these profiles achieves under various simulation assumptions. The different colored lines and shading for the interquartile range show the different permeability types. As should be expected, the high performers generally do best, low achievers worst, and other profiles somewhere between. However, depending on permeability type and built-in simulation assumptions, some striking dynamics become clear.

In all permeability types, and under all simulation parameters, the lowest-endowed students have the lowest activated skills. Improving permeability is not a sufficient lever to consistently improve outcomes for individuals whose latent skills are low to begin with. Mid-range students show a somewhat larger variation depending on permeability type: here, it is clearer that more permeable education types lead to higher activated skills, though the range is comparatively narrow and the interquartile ranges overlap in almost all simulation assumptions. Moreover, as the assumptions become more “realistic”, the outcomes between different permeability types also narrow. For students whose achievement is average, then, permeability makes at most a marginal difference.

Figure 4: Skill activation by latent skill profile



Note: Lines show average skills activated in a simulation and permeability type for individuals in each group. Colored lines differentiate different groups of individuals by ability level in type A and B latent skills. Shaded areas show the 95% confidence interval for each group. The x axis shows different permeability types from the most to least permeable. Each individual graph represents a different simulation based on the varying parameters shown in table 1.

These patterns change when looking at high performers, and at students who may have a high endowment of one kind of skill but not of another. High-performing students, in all cases, have high activated skills under all assumptions and in all permeability types. However, dead-end permeability types seem to disadvantage high-performing students – with mean activated skills on average lower, and a higher interquartile range than other permeability types. In general, however, total activated skills are high in all simulations, and it can be concluded that highly endowed students will generally highly achieve no matter how permeable the education system is.

The most striking results come in the ideal types where an individual has a high skill endowment of one type but a low endowment of another. In these cases, the permeability type has large impacts on the total activated skills under certain assumptions. In general, an individual with high latent A skills will have high activated skills no matter what the permeability type and simulation assumptions, though the interquartile range on these values expands greatly for all permeability types as simulation assumptions are loosened towards a more realistic setting. Nevertheless, it is the assumptions underpinning the simulations, rather than the permeability types themselves, that have the greatest impact on the activated skills in these cases.

For individuals with a high endowment of B skills, but low A, on the other hand, the level of permeability has a clear impact on activated skills. In these cases, fully permeable and silo types have clearly better skills activation outcomes, followed by the two bottleneck types, with one pathway and dead end types being the least effective in activating skills. Though the differences diminish somewhat through the simulation assumptions – at least in terms of the interquartile ranges the difference in activates skills in between a fully-permeable or silo type and a one pathway or dead-end type is in some simulations up to 50 of a possible 100 points. This makes clear the negative effect of a lack of permeability on individuals more endowed with type B than type A skills – in a non-permeable system, even very high B skills are not enough to compensate for a lack of A. Non-permeable types are systematically unfair to this group of individuals.

Economically speaking, these results demonstrate both inefficiency and inequity of skills activation where education systems become less permeable and assumptions are relaxed. Indeed, these results may be considered to model the deadweight loss that comes about when both permeability is reduced and when assumptions are relaxed to model non-completion and imperfect information. In each case, skill supply is reduced such that the market skills equilibrium shifts to the left, depriving the labor market of skills that may have been available in more permeable models.

Discussion

The simulations in the demonstration are much more useful for showing the limitations of what could possibly happen in a perfect world than they are for considering what might happen in the real world. Indeed, there is a conflict in the literature between empirical work comparing returns to education by type and work that looks at tracking. This section considers how permeability might help resolve those two divergent literatures, how this relates to the conversation on systemic (in)equity, and what new issues it uncovers.

Research on countries with permeable education systems finds that both types—typically academic and vocational education in those contexts—generate similar returns. For example, one study in Switzerland shows how individual returns to education vary depending on years of education and according to field of study much more than depending on education type (Pfister et al., 2015). Similar research in Finland finds that vocational education has positive and long-lasting effects on wages, especially for those who expressed a preference for vocational education when applying. The causal literature on returns to education and productivity from high-permeability systems would seem to align with our findings that increased permeability is good for overall productivity and individual returns to education.

In contrast, research from countries with less permeable education systems has historically found negative—and often racialized—effects of "tracking," "streaming," or "ability grouping". In the mid- and late 20th century in countries like the US and UK, vocational education was often the lower-track option and research blamed it for increasing high school dropout and decreasing the chance of university attendance (Ainsworth & Roscigno, 2005). Oakes (2005, original publication 1985) famously argued against the tracking students into vocational and other programs, pointing out how the practice perpetuated racial and class-based inequalities. As summarized by Gamoran (2009), this literature tended to find that tracking decreased overall productivity while increasing inequality because the gains made by high achievers were offset by larger losses among low achievers. In sum, the tracking literature would seem to argue that increased permeability decreases productivity and equity.

Taking a permeability perspective can help resolve this apparent contrast—some studies showing the value of various education types while others decry the inherent inequity and inefficiency of sorting students—in at least two ways. First, a major weakness of the tracking literature is that it tends to employ non-causal methods. This is partially due to the time most of this research was conducted and its orientation towards the sociology and education policy literatures. It is also a function of the low-permeability systems in which the research was conducted. Even with the intention and technology to attempt causal methods, it is impossible to hold years of education constant when comparing education types if the system limits years of education in one pathway.

Second, and related to the first issue, the effect of an education program comes from both its direct impact on skills and its indirect impact on access to additional education programs later in life (Heckman et al., 2014). When programs do not offer access to additional levels, their returns are lower. Not only does a lower-permeability education system create a downward bias in measuring the return on education for non-dominant programs because of poor comparison groups, it lowers the returns to non-dominant programs that lack or limit access to further education options.

Taken together, these two problems indicate that the different conclusions of the literature from permeable education systems comparing returns to education by type and the literature from less permeable education systems on tracking may come about at least partially because the research is done in education systems with different permeability models. Lower permeability downward-biases measurements of returns to education in the non-dominant program type while reducing the real returns to education in the non-dominant program. As a result, research in less permeable systems necessarily finds that the non-dominant type of education has lower returns while research in more permeable systems can find that type is not the main driver of returns to education.

However, permeability is not the only issue at play. The conflicting findings on returns to education by type also uncover two important issues related to permeability—the role of quality and the meaning of program types. Program quality is a central and important assumption in our model of permeability. We argue that programs activate more of the matched skill type than the mismatched skill type. We model this by specifying a high range of skill activation for matching programs and a lower range for mismatched programs. Importantly, we model both education types as equally effective on average for their respective matched and mismatched skills. This may not always be the case. Another important source of the low returns observed in the tracking literature is program quality—the lower-level programs often had less resources and lower-quality curricula (e.g. Ainsworth & Roscigno, 2005; Oakes, 2005). If program quality is low—especially if it is low only in one education type—then the returns to education are necessarily. Permeability might mean that students can leave a pathway or avoid it altogether, but it cannot make up for low program quality.

The second issue raised by this discussion is the question of what we mean by education types. We have deliberately avoided specifying this in the theory because we believe it is a fertile area for future research, but the difference between the two literatures highlights the issue. The returns to education literature is almost entirely focused on academic and vocational education. In contrast, the tracking literature does not always differentiate between high- and low-level versions of the same curriculum vs. a college prep and vocational pathway. This distinction matters—vocational education serves a different purpose from academic university preparation programs, while high- and low-level versions of the same curriculum do not (Gamoran, 2009).

We can find some guidance about what education types might and might not be in the literature. First, different types of programs are not aligned with learning styles (e.g. visual learners vs. auditory learners), which have been debunked in the psychology literature (Pashler et al., 2008). In contrast, there is strong causal evidence that learning places matter for outcomes—vocational education and training programs that include work-based learning have positive impacts on a range of youth labor market outcomes while school-based programs do not (Bolli et al., 2021). At a slightly more macro level, vocational and academic programs might be differentiated based on student preferences for theoretical vs. practical content, or they might be differentiated based on student motivation for university vs. career/professional prospects. These are difficult to differentiate empirically, but there is some causal evidence that individual students have heterogeneous returns to education. For example, Balestra and Backes-Gellner (2017) show that returns to vocational vs. academic education vary along the wage distribution. Understanding what it takes for programs to serve different student needs will be fundamental to applying permeability in real-world settings.

In sum, we find that permeability can explain some of the existing disagreements in the literature and even arguably contributes to diverging observations about returns to education by type in different permeability models. At the same time, however, we emphasize that permeability alone is not sufficient for desirable education outcomes. Program quality is foundational. Furthermore, understanding more about what differentiates program types will be critical to applying the concepts presented here.

Conclusions

Building on the empirical and theoretical literatures related to the returns to education by skill type, we provide a theoretical model relating education system permeability—the availability of multiple program types at multiple levels along with transitions among them—to skill development and individual returns to education. We find that education system models with higher permeability have greater capacity to generate more skills in total and can better serve students whose skills align with the non-dominant type of education. More permeable systems could be better able to match labor market demand when a variety of skills at higher levels are needed.

We show that the structure of the education system—specifically its permeability—enables or limits its potential skills output at a population level and impact on students at an individual level. Even in a frictionless perfect world, it is not possible for less permeable education systems like the one-pathway or dead-end models to generate high-level skills in the non-dominant type. Individuals with moderate or even high total ability levels cannot reach moderate or high levels of activated skills in less permeable education systems if their skills do not align with the dominant type of education. Permeability is necessary for maximizing student and social returns to education.

Permeability contributes to the attractiveness of non-dominant programs and makes their value more measurable. Greater access to further education—increased by both the availability of further programs in all types and the possibility of transition between programs—increases returns to education. The opportunity to pursue each program type up to the highest education levels enables accurate type-based comparisons in research. At the same time, extremely high quality in a low-permeability system cannot solve all the problems of low permeability. We find that there is a limit to what program-level interventions can achieve unless they are in permeable systems.

However, while permeability might be necessary for certain outcomes, it is not sufficient. In other words, higher permeability alone does not cause increases in skills output or individual outcomes. The structure of the system creates or removes limitations on what the system can potentially achieve but does not drive that achievement. One-pathway systems limit the options and opportunities of students, but adding low-quality programs of another type will not solve that problem.

The main contribution of this paper is to enable further research that uses permeability as a lens to consider education-system outcomes. We provide an empirical definition of permeability and theorize its relationship to outcomes. We do not specify what different types of education might be, so further research can consider that question. The ideas put forth in this paper should be tested as rigorously as possible to determine if they hold true in reality. There is increasing recognition in scholarship and the popular media that many education challenges are systemic rather than programmatic. This avenue of research offers one way of looking at systemic factors in education.

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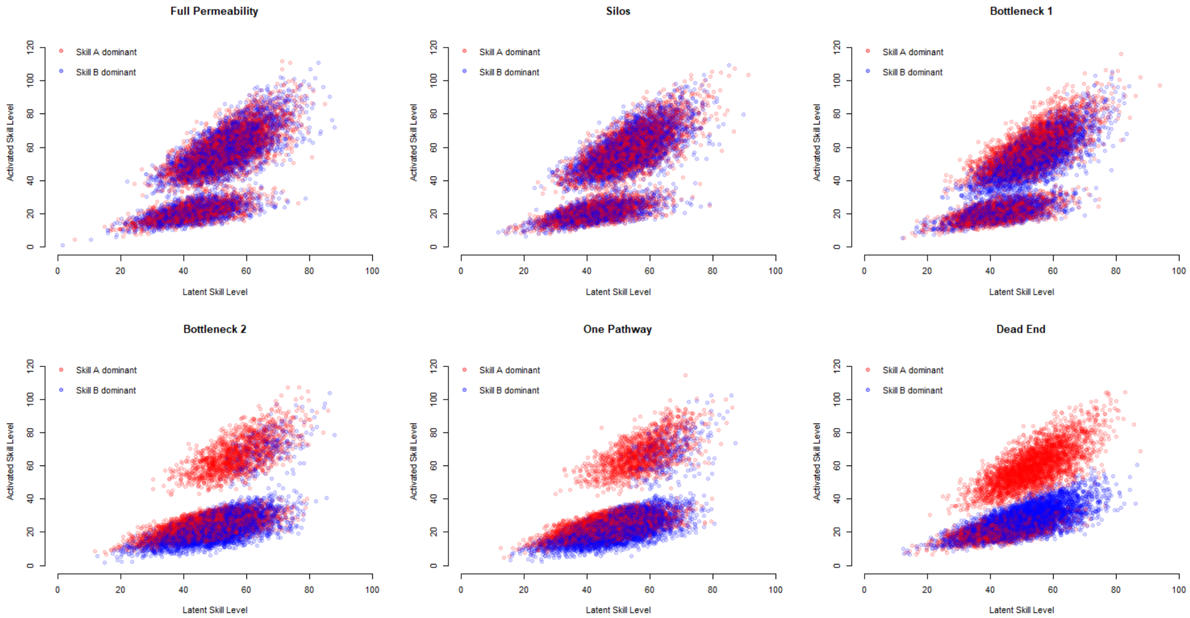
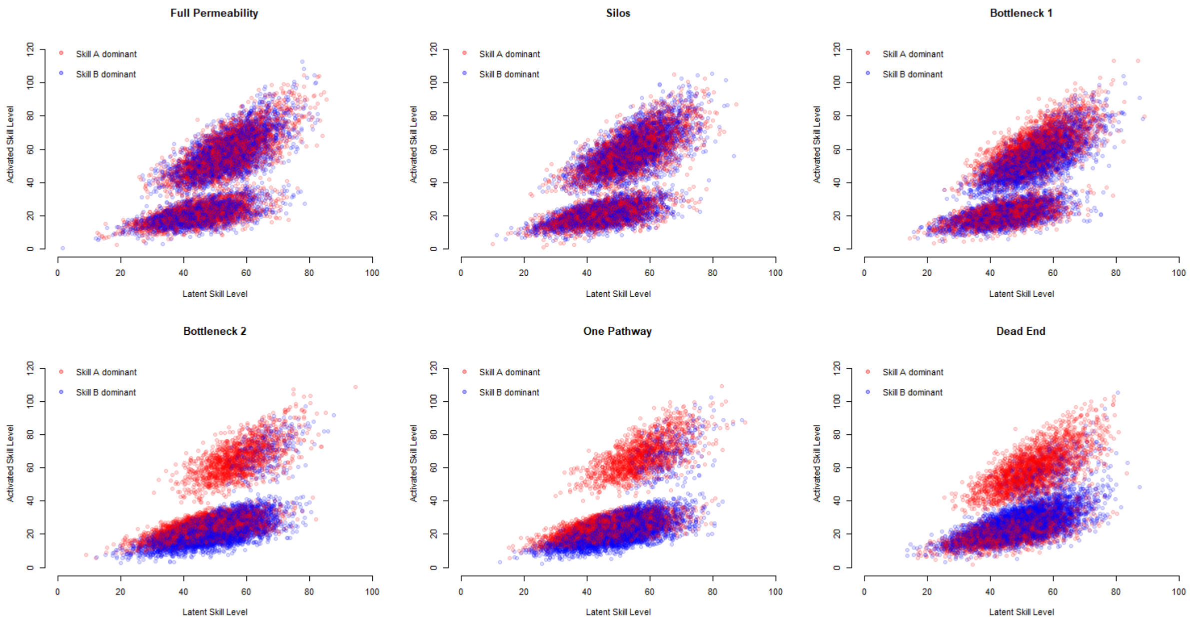
Appendix 1: Scatterplots for all simulations

Figure 5: Individual skill activation by permeability model, non-completion allowed (perfect information)



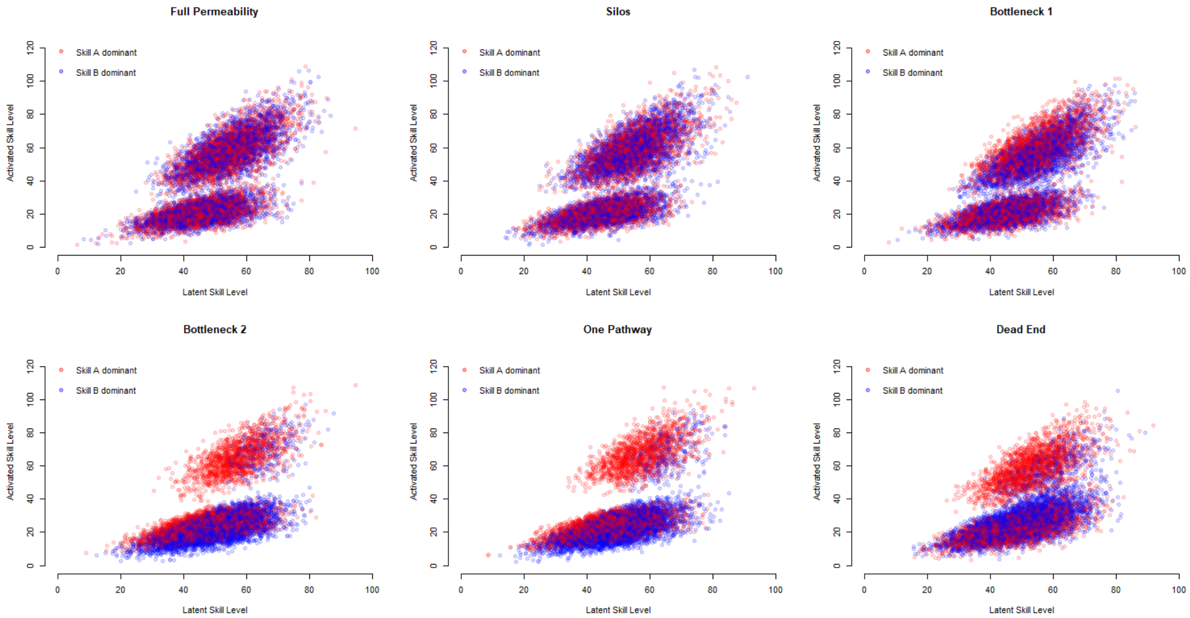
Note: red dots are individuals dominant in latent skill A, blue dots are individuals dominant in latent skill B. The x-axis shows total latent skill level and the y-axis shows total activated skill level after secondary and tertiary education (if available). This figure shows results in a world where individuals have perfect information to choose the education program that matches their dominant skill type but only those with total activated skills higher than 25 continue to tertiary education.

Figure 6: Individual skill activation by permeability model, non-completion and imperfect information allowed



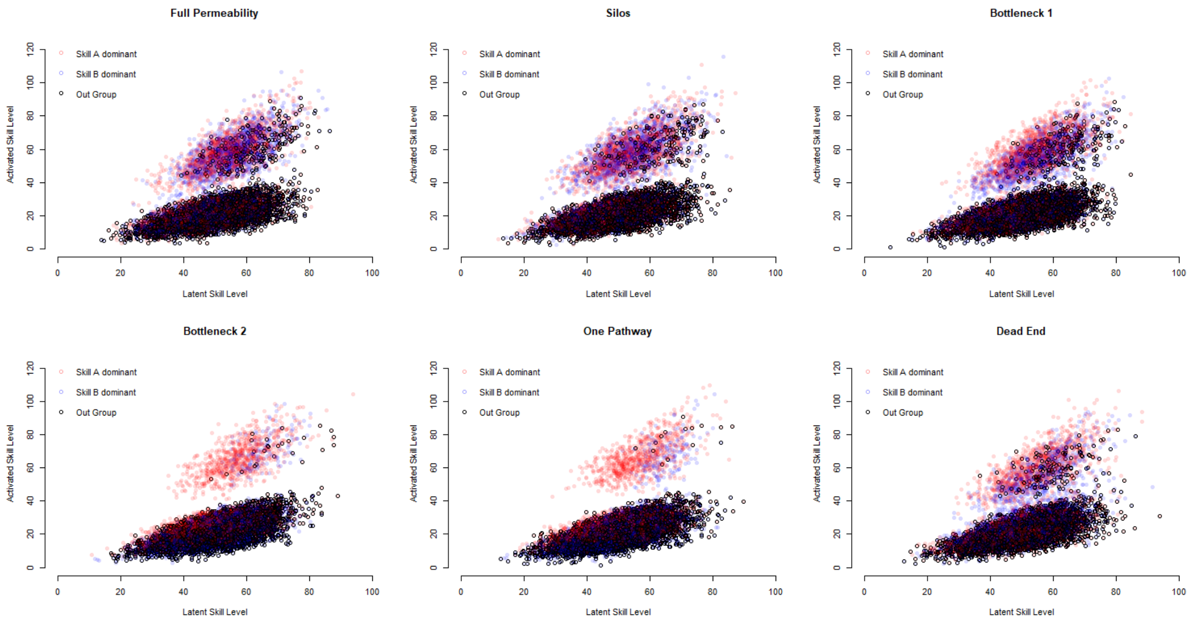
Note: red dots are individuals dominant in latent skill A, blue dots are individuals dominant in latent skill B. The x-axis shows total latent skill level and the y-axis shows total activated skill level after secondary and tertiary education (if available). This figure shows results in a world where 75% of individuals have perfect information to choose the education program that matches their dominant skill type, and 25% are randomly allocated to education types. Only those with total activated skills higher than 25 continue to tertiary education.

Figure 7: Individual skill activation by permeability model, information is worse at the lower education level



Note: red dots are individuals dominant in latent skill A, blue dots are individuals dominant in latent skill B. The x-axis shows total latent skill level and the y-axis shows total activated skill level after secondary and tertiary education (if available). This figure shows results in a world where 62.5% and 75% of individuals have perfect information to choose the education program that matches their dominant skill type at level 1 and level 2, respectively. Only those with total activated skills higher than 25 continue to tertiary education.

Figure 8: Individual skill activation by permeability model, systemic discrimination added



Note: red dots are individuals dominant in latent skill A, blue dots are individuals dominant in latent skill B. The x-axis shows total latent skill level and the y-axis shows total activated skill level after secondary and tertiary education (if available). This figure shows results for a simulation that includes an in-group and out-group (outlined dots). For the in-group, 62.5% and 75% (out-group: 50% and 62.5%) of individuals have perfect information to choose the education program that matches their dominant skill type at level 1 and level 2, respectively. Only those with total activated skills higher than 25 (out-group: 35) continue to tertiary education. Education is slightly less effective for the out-group: matched programs activate between 50-100% of skills for the in-group (40-90% for the outgroup) and mismatched programs activate 0-50% of skills for the in-group (0-40% for the out-group).