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DISCUSSION PAPER SERIES 159/25

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www.rfberlin.com

DECEMBER 2025

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Reference

JEL Codes: I21, C35, C53

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Recommended Citation: Hessel Oosterbeek, Tina Rozsos, Bas van der Klaauw (2025): School choice, school switching, and optimal assignment. RFBerlin Discussion Paper No. 159/25

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School choice, school switching, and optimal assignment

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Abstract

Close to 20% of secondary school students in Amsterdam – and elsewhere – transfer between secondary schools at some point, even when initially placed in their most-preferred school. School switching is costly for the students involved and disrupts the learning environment of their former and new classmates. Using data from the Amsterdam secondary-school match linked to administrative registers, we show that switching can be predicted by hard-to-rationalize initial school choices. Over 60% of switchers can be correctly identified at the admission stage. Simulations indicate that encouraging predicted switchers to adjust their preference ranking of schools could reduce the switching rate by almost 15%.

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Version December 10, 2025

*We thank seminar and conference participants in Amsterdam, Brno, and Catanzaro for their useful comments. We acknowledge financial support from an Open Competition L grant from the Dutch Science Foundation (NWO). The non-public microdata used in this paper are available via remote access to the Microdata services of Statistics Netherlands.

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1. Introduction

Since 2015, secondary schools in Amsterdam assign students to schools using the deferred acceptance (DA) mechanism. The school district evaluates this system mainly in terms of the ranks that the assigned schools have on students' rank-ordered lists (ROLs) – for example, the share of students assigned to their first, second, or third choice. Such evaluations assume that students are fully informed about school attributes and how well each school fits them. This assumption is questionable: nearly 20% of students placed in their most-preferred school switch schools at some point during secondary education (Ketel et al., 2023).[1]

This paper examines whether school switching can be predicted at the admission stage in the form of hard-to-rationalize initial school choices, and evaluates policies that aim to reduce school switching by improving initial school assignments. We combine data from the Amsterdam secondary-school match with register data to estimate rich school demand models. Based on these demand models, we compute predicted school choice probabilities for every school in each student's choice set. When students rank a school with a low predicted choice probability as their most preferred school, we classify that choice as hard-to-rationalize, because students with such preferences must have a large idiosyncratic utility component for their chosen school to rationalize their choice. Hard-to-rationalize preferences may imply low student-school match quality and signal application mistakes, due to, for example, imperfect information about school characteristics (Narita, 2018; Larroucau et al., 2025). Predicted school choice probabilities may capture then match quality better than students' own rankings.

We find that students with lower predicted choice probabilities at their most-preferred school are significantly more likely to switch schools, and over 60% of switchers among students placed in their top-ranked school can be predicted at the moment of admissions. These results provide a more nuanced understanding of switches than previous studies, which focus on identifying social groups that are more likely to switch schools (Calibuso and Winsler, 2021; Prior and Leckie, 2022). Our findings show that school switching is not only related to student characteristics but also reflects predictable mismatches in the school choice of students.

Next, we assess the potential effects of three different changes to the school assignment mechanism that aim to reduce school switching. The first change replaces the random lottery numbers that are normally used to break ties with priorities based on either predicted

[1] This rate is comparable to switching rates in other densely populated urban areas, where it is common to see 20% of all middle/secondary school students switching schools at least once. Observed switching rates in middle/secondary school in the period 2002–2019 include 19% in Miami (Calibuso and Winsler, 2021) and 21% in inner London (Strand and Demie, 2007). In less dense areas, switching rates are lower: 12% in England (Prior and Leckie, 2022), 14% in Colorado, and 15% in Rhode Island (Rumberger, 2015). Switching is more common for younger students, and in settings with financial or informational constraints: Grigg (2012) reports 37% in Nashville primary schools and Ajayi et al. (2025) report 35% in Ghanaian secondary schools.

school choice probabilities or on predicted switch probabilities. The second change removes schools with high predicted switch probabilities from students' ROLs. This policy simulation provides an upper bound to what could be achieved by an information intervention that discourages students from applying to schools that they are likely to leave. The third change adjusts the ROLs of future switchers by replacing the initial placement school by the switch destination school; this simulation is used as a welfare-improving benchmark. We evaluate each of the three changes in terms of their impacts on: (*i*) the average placement rank (on both the original and the adjusted ROLs); (*ii*) the average predicted choice probability at the placement school; (*iii*) the average predicted switch probability at the placement school; and (*iv*) school segregation by academic performance, ethnicity and parental income. Removing schools where students have high predicted switch probabilities from their ROLs is the most promising policy. It reduces the predicted school switching rate by 15%, with only minor changes in the average placement rank and in the resulting between-school segregation.

School switching is associated with disrupted learning, time, effort, and adjustment costs, and in some cases with worse long-run academic outcomes (Canpolat and Atli, 2021; Gasper et al., 2012; Langenkamp, 2016; Rumberger, 2015; Schwartz et al., 2017; Welsh, 2017). Switching also disrupts the learning environment of switchers' former and new classmates, potentially harming their school performance. In addition, if switchers leave popular schools, their seats could have been assigned to students who may have stayed at the school. Ensuring that students enroll in well-fitting schools from the beginning can reduce switching and its associated negative impacts.

This paper connects the literature on school choice with the hitherto unconnected literature on school switching. The school choice literature consistently finds that students dislike a larger home-school distance and have a preference for schools with a larger share of students from similar backgrounds (Beuermann et al., 2023; Denice and Gross, 2016; Jochim et al., 2014; Ruijs and Oosterbeek, 2019; Oosterbeek et al., 2021; Glazerman and Dotter, 2017; Munteanu, 2024). The literature on school switching emphasizes differences in the switching rates across social groups, differences in the academic and social composition between the origin and destination schools, and the role of information in motivating switches (Calibuso and Winsler, 2021; Carlson et al., 2018; Narita, 2018; Welsh, 2017). To the extent that the two sets of determinants are overlapping, school switching reveals a poor initial school choice. The strong association that we find between hard-to-rationalize school choices and subsequent switching indicates that this overlap is substantial. School choice and school switching can therefore be seen as two sides of the same coin.

The rest of this paper is organized as follows. Section 2 describes the institutions around school assignment and school switching in the context of secondary schools in Amsterdam. Section 3 presents the data. Section 4 describes how we estimate predicted school choice probabilities and their use in predicting school switching. Section 5 reports and discusses the results. Section 6 presents the results from the policy simulations. Section 7 concludes.

2. Institutional background

This section outlines the secondary school system in the Netherlands, explains how students in Amsterdam are assigned to secondary schools, and describes how students can switch schools.

Students enroll in secondary school around the age of 12. In the final year of primary school, the teacher provides an ability track recommendation based on a student's academic performance in primary school. The final recommendation takes into account the results of the nationwide standardized test that all students take in the final year of primary school. The teacher's recommendation is binding: students can only apply to secondary schools that offer the recommended track. Beyond that, students have free school choice, and schools cannot select students on, for example, prior academic performance or home-school distance. Almost all students enroll in schools that are publicly funded and inspected by a national authority. To alleviate inequalities, schools receive additional funding for students from disadvantaged backgrounds.

Secondary schools are organized into four ability tracks: the four-year vocational-elementary and vocational-theory tracks that prepare students for vocational college, the five-year college track that prepares students for universities of applied sciences, and the six-year university track that prepares students for research universities.[2]

Schools decide which tracks they offer. Some schools offer only one track (single-track schools), while others offer multiple or even all tracks. Schools offering multiple tracks may initially group students from different tracks in the same class and use the same study material in the first (and second) year. This allows students to easily transfer between tracks. Gymnasium is a special case within the academic track, requiring students to additionally take the classical languages Latin and Greek. A few schools only offer gymnasium, and students who no longer wish to take Latin and Greek must switch to a school offering the regular university track.

Amsterdam is the largest school district in the Netherlands, with approximately 65 secondary schools admitting around 7,500 students annually. A centralized system is used to admit students to secondary schools. Students submit a ROL of their preferred schools consistent with their track recommendation. There is considerable competition for places in popular schools, particularly in the college and university tracks. Schools in Amsterdam are well connected to public transport and generally reachable by relatively short bicycle rides. While home-school distances can affect individual preferences, distances between schools are not large enough to exclude schools from students' feasible choice sets.

During our observation period, the DA mechanism (cf. Gale and Shapley, 1962) was used

[2]The vocational-elementary track combines two tracks. Schools in our sample that offer one of these also offer the other, often in mixed classes.

to assign students to secondary schools.[3] Schools may apply a limited number of priority rules, which only apply to the highest-ranked school on the ROL. Students with siblings at the school and applicants to special programs, such as Montessori or Dalton schools, who attended a primary school with the same teaching approach receive priority. Random lottery numbers are used to break ties within priority groups. A key advantage of the DA mechanism is that it is strategy proof, students are best off submitting a ROL that reflects their true preferences.[4] The ROLs can thus be used to analyze the determinants of school preferences and the welfare effects of different allocations (cf. De Haan et al., 2023).

Students not assigned to their most-preferred school are placed on the reserve lists of all schools they ranked above the school where they are placed. If places become available before the start of the school year, for instance because a student moves to another city, these places are offered to students on the reserve lists. We consider these reserve list-based improvements as part of the school assignment outcome. We take the school in which the student actually starts in the first year of secondary school as the initial placement school, and subsequent school switching is relative to this school.

School switching can occur at any moment. The Amsterdam school district does not operate a centralized system to manage switching. This is similar to other school districts around the world. Schools are not obliged to accept students who wish to switch schools, even when they have unfilled capacity. Schools that are popular during the initial school assignment often do not accept students who want to transfer to their schools in a later stage of secondary education. Parents and students have to manage the school switching process themselves, which involves contacting schools to check for opportunities to transfer and handling the administrative tasks to register their student at the new school. There are no monetary costs associated to school switching, but it often requires a substantial time investment from parents.

3. Data

This section presents our data sources, describes the construction of variables and presents descriptive results.

We use register data from the Amsterdam secondary school match for the years 2015 to 2020. For participating students, we observe their track recommendation, ROL, randomly assigned lottery number(s), assigned school, and a range of background characteristics including their score on the nationwide exit test at the end of primary school. These data are merged within the Microdata environment of Statistics Netherlands to other administrative records on school enrollment and on school and student characteristics.

[3]The DA mechanism is widely used in student-school matching. Variants are currently also in place in large school districts such as New York City and Boston (Abdulkadiroğlu et al., 2017).

[4]In recent years a few details were introduced in the assignment mechanism that allow for strategic behavior. Antonello et al. (2025) show that students are largely naive and truthful when submitting their ROLs.

The track recommendation determines the choice set of a student. A few schools have multiple programs within the same ability track, for example a regular program and a bilingual or sports program. We merge these programs and within each ROL only keep the highest-ranked program so that each school appears at most once in a ROL.

Statistics Netherlands observes for each student the school enrollment on October 1st.[5] We define a school switch as a change in school enrollment between two consecutive years in which the student remains in secondary education. School enrollment data are available until 2023, and not all cohorts in our sample have completed secondary school by that time. Most switching occurs, however, in the first two years of secondary education and these years are observed for all cohorts (see Figure A.1 in Appendix A).[6] There were no school closures during our observation period, but some schools were renamed. In these cases, we classify students who do not follow the main student body as switchers. Students who drop out of secondary school are not considered switchers.

Merging the application data with administrative records at Statistics Netherlands provides a rich set of student and school characteristics. We construct home-school distances and observe the standardized score on the primary school exit test, household income percentile, immigrant status, schools attended by older siblings, and secondary school enrollment of primary school classmates. We use student characteristics to assign students to socioeconomic groups and to characterize the composition of secondary schools.

We drop about 1% of the students because their home-school distances cannot be computed or information on household income is missing. Due to the Covid-19 pandemic, there were no primary school exit tests in 2020. For missing test scores we impute the average test score for students with the same track recommendation and we have an indicator for missing test score. Statistics Netherlands does not have individual data on educational attainment for older cohorts or individuals who did not attend school in the Netherlands. We construct an indicator for missing parental education.

Table 1 presents summary statistics for the students in our sample. About 18% of the students switched schools at least once during secondary education. The college and university tracks are the most common, with close to 30% of the students each. The other students are close to equally split between the two vocational tracks. Students list on average 7.45 schools on their ROL; 84% were placed on their most-preferred school and about 4% were placed outside their top three. The average home-school distance is slightly over four kilometers. Results from the nationwide exit test from primary school is missing for 19% of the students, mainly from the 2020 (Covid-19) cohort.

[5] School funding depends on the number of enrolled students on that date.

[6] We focus on the first school switch of a student. Figure A.1 in Appendix A shows that most switchers change schools only once. Fewer than 2% switch more than twice.

Table 1. Descriptive statistics

Variable	Mean	SD
Switched schools	0.18	
ROL length	7.45	3.78
Placement rank		
1	0.84	
2	0.08	
3	0.09	
4	0.01	
5+	0.02	
Track		
vocational-elementary	0.20	
vocational-theory	0.23	
college	0.29	
university	0.28	
End test score (standardized)	-0.01	0.98
End test score missing	0.19	
Home-school distance (placement school)	4.08	4.91
Home-school distance (top-ranked school)	4.10	4.92
Female	0.51	
Immigration background		
Dutch	0.41	
First generation immigrant	0.06	
Second generation immigrant	0.54	
Origin region		
Netherlands	0.41	
Western country	0.19	
Non-Western country	0.37	
unknown	0.04	
Household income (percentile)	0.62	0.27
Mother university education	0.38	
Mother education missing	0.19	
Father university education	0.31	
Father education missing	0.34	
N = 42,782		

About half of the students are female and the majority is classified as second-generation immigrants. The average household income percentile is 62, reflecting that households in Amsterdam often have a higher income than other households in the rest of the country. Parental education is more often missing for fathers than for mothers, and a larger share of the mothers than of fathers has completed university education.

Table 2 shows the shares of winners of the admission lottery by track, and the shares of switchers by track and lottery result. It reveals that the share of lottery winners is larger in the vocational tracks than in the college and university tracks. School switching is more prevalent among lottery losers than among lottery winners. Yet school switching is also common among lottery winners and occurs most frequently among students in the vocational-theory track, where almost one in four students change schools.

Table 2. Admission lottery winners and school switchers across tracks

Track	# students	% lottery winners	% switch (winners)	% switch (losers)
vocational-elementary	8755	94.8%	13.5%	18.3%
vocational-theory	9944	89.6%	22.5%	25.5%
college	12228	77.4%	18.5%	22.0%
university	11855	78.4%	13.6%	18.1%

Table 3 compares the rank of the switch destination school to the rank of the initial placement school, separately for lottery winners and lottery losers. It shows that lottery winners and lottery losers are almost equally likely to switch to a lower-ranked school, to a school they did not rank on their ROL at all, or to a school that did not participate in the Amsterdam secondary-school match. Only 3.1% of lottery losers switch to higher-ranked schools. Those are the only students whose switch is consistent with their initial revealed preferences.

Table 4 distinguishes different switch categories defined by the co-occurrence of switching with one or more of the following events: low academic performance (grade retention or move to a lower track), residential move, move to a higher track, and change from a single to a multi-track school. More than half of all switches does not occur jointly with one of these

Table 3. Ranking of switch destination compared to initial placement

Switch destination	% lottery winners	% lottery losers
Better ranked than placement school		3.1%
Worse ranked than placement school	4.1%	4.1%
Unranked lottery school	8.5%	9.3%
Not lottery school	4.1%	3.2%
Total number of students	34599	6202

Table 4. Categories of school switching

Switch category	% switches
Uncategorized	52.9%
Low performance	25.0%
Residential move	4.9%
Move to higher track	3.6%
Single-track to multi-track school	3.4%
Low performance + Single-track to multi-track school	4.3%
Level change within uni track + Single-track to multi-track school	3.2%
Low performance + Residential move	1.9%
Level change within uni track + Low performance + Single-track to multi-track school	0.4%
Level change within uni track + Residential move + Single-track to multi-track school	0.2%
Low performance + Residential move + Single-track to multi-track school	0.2%

events. For almost a third of the switches, we observe signs of low academic performance, often in combination with other events. In 12% of the cases, students switch from a single-track to a multi-track school, and about 7% of the switches coincide with a residential move. Less than 4% of the school switches involve a move to a higher track level.

4. Methodology

This section first formulates the rank-ordered logit model used to analyze school demand. It then links the school choice probabilities derived from this demand model to a logit model for school switching.

Rank-ordered logit models have long been used to describe individual discrete choices (Chapman and Staelin, 1982; Punj and Staelin, 1978). They are commonly used in school choice settings where students' preference rankings are observed (e.g.: De Haan et al., 2023; Oosterbeek et al., 2021; Denice and Gross, 2016; Beuermann et al., 2023). Let U_{ij} be the utility of student i for school j, which depends on student-school characteristics Z_{ij}, school fixed effects ϕ_j, and an unobserved utility component ε_{ij}:

$$U_{ij} = Z'_{ij}\gamma^G + \phi_j^G + \varepsilon_{ij}, \tag{1}$$

To allow for heterogeneity in preferences across social groups G, we let the model parameters vary by group (cf. Oosterbeek et al., 2021). A social group is defined by the combination of the student's track recommendation, immigration background and gender.[7] The set of

[7]Table A.3 in Appendix A shows the sample sizes corresponding to the social groups. Group sizes vary

student-school characteristics Z_{ij} includes home-school distance and interactions of characteristics of the students and the schools. Table A.1 in the appendix presents a complete list. Variables with zero variance within a social group are excluded. The rank-ordered logit model follows from the assumption that unobserved utility component ε_{ij} follows an i.i.d. type-I extreme value distribution.

Using the estimated parameters, we predict for each student the probability of ranking each school in their choice set as their top choice. High predicted choice probabilities for highly ranked schools indicate that a student submitted a ROL that is well aligned with the choices of peers in the same social group G. Conversely, low predicted choice probabilities for highly ranked schools suggest hard-to-rationalize choices, as they require large values of unobserved utility component ε_{ij}.

In the next step, we include the predicted choice probability at the placement school in a logit model for predicting later school switching. In addition to the predicted choice probability, the model includes student characteristics and fixed effects of placement schools.[8]

When estimating this model, we restrict the sample to students who enrolled in their most-preferred school. For these students, any subsequent switch implies a deviation from their initially expressed demand for schools, which may reflect an initial application mistake. Our switching model only uses information available during the initial application stage, thereby replicating the decision-making environment of students. With this restriction, a negative coefficient for the predicted choice probability suggests that switches are not driven by real demand changes, but by hard-to-rationalize initial preferences. To examine whether this distinction is relevant, we repeat the analysis for all switches, and for sub-samples of switches that did or did not co-occur with residential moves or signals of low academic performance. Although there may be other reasons for real demand changes, residential moves and low performance are probably the main ones.

5. Results

This section first presents results on the predicted choice probabilities based on the estimated school choice models. We then use the choice probabilities to predict school switching.

5.1. School choice

We compute predicted choice probabilities for every school in each student's choice set based on our estimated rank-ordered logit models. The upper left panel in Figure 1 displays the distribution of these predicted choice probabilities, grouped by the true rank of each school on a student's ROL. Recall that a higher predicted choice probability means that the school is more likely to be the student's most-preferred school. The average choice probabilities

between 945 and 3602 students, with on average 30 schools in the choice set of each student.

[8]Including school fixed effects assumes that baseline switching rates are stable within schools over time. Figure A.2 in Appendix A confirms that switching rates vary little for most schools.

decline monotonically with the rank on the ROL, but the distribution of predicted choice probabilities is noisy, suggesting that the unobserved random utility component plays an important role.

We can translate the predicted choice probabilities into predicted ROLs by ranking schools on the ROL according to the predicted choice probabilities. The bottom left panel of the figure shows the distribution of predicted ranks per observed rank. There is a clear positive correlation between the observed ranks and the predicted ranks, but this relation is far from perfect.

The right panels of Figure 1 compare switchers and stayers. Switchers have on average significantly lower predicted choice probabilities for their most-preferred school, suggesting a higher degree of mismatch. There is no significant difference in the predicted rank of the most-preferred school.[9]

5.2. School switching

When predicting school switching, we restrict the sample to admission lottery winners who complied with their placement.[10] This selection removes the confounding effect of having lost the lottery from the switching decision.

Table 5 presents the estimates from the logit model that relates the predicted choice probability at the placement school to subsequent switching. Column (1) presents the estimates for a specification that includes only the choice probability and placement school fixed effects. The estimated coefficient on the predicted choice probability is negative and highly significant: within a school, the students with the lowest choice probability at that school are most likely to switch schools later. These are the students for whom this initial school choice was hardest-to-rationalize.

Column (2) adds social group fixed effects to account for differences in school switching rates across groups. The estimated coefficient on the predicted choice probability becomes more negative. Column (3) adds further student characteristics;[11] the choice probability coefficient hardly changes. In the most complete specification, a one percentage point increase in the predicted choice probability corresponds to a 2% decrease in the subsequent switch probability ($1 - 0.115^{0.01}$).

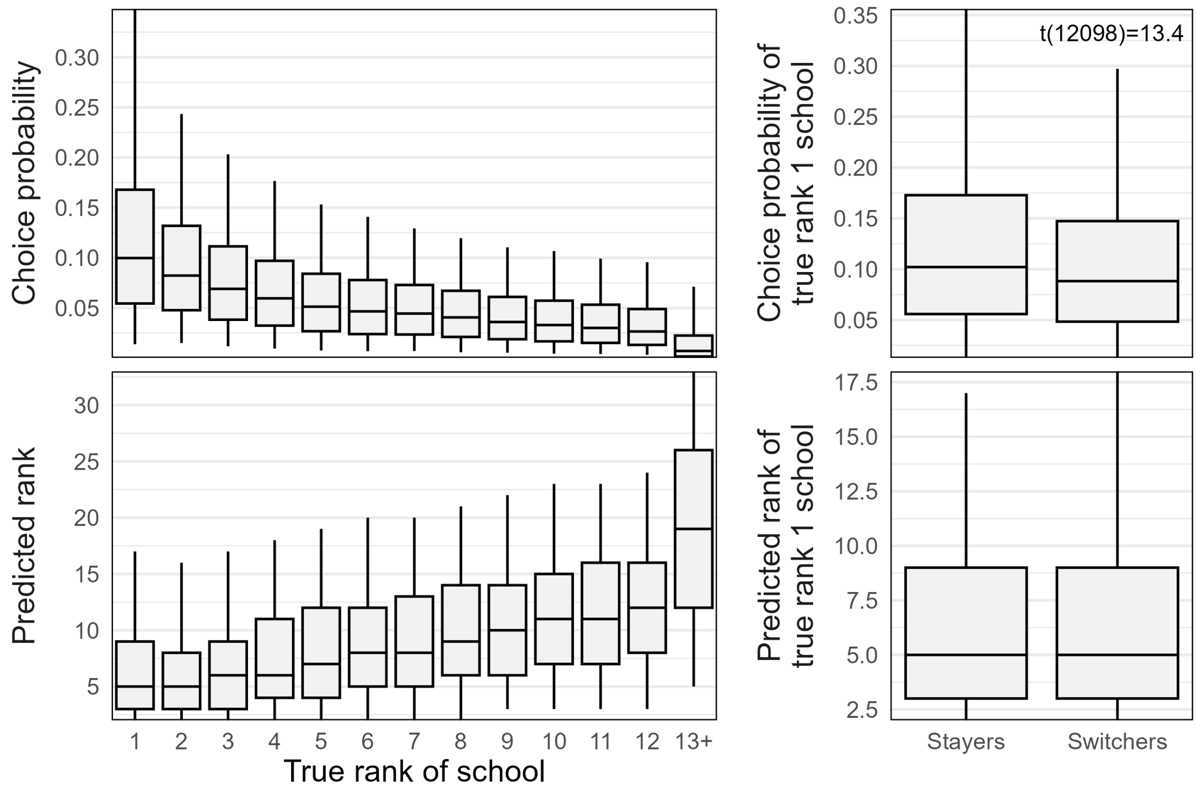
To evaluate the predictive performance of the models, we report accuracy, sensitivity, and specificity. These measures are all around 0.65, which implies that the model correctly identifies almost two-thirds of the observed switchers (sensitivity), and a similar share of observed non-switchers (specificity). The comparison across the three specifications shows

[9]As a robustness check, Figure B.1 in Appendix B presents the same results as Figure 1, using a set of school characteristics instead of school fixed effects. This makes the correlation between the observed ranks and predicted choice probabilities somewhat weaker, but the same general patterns hold.

[10]Compliance with the admission lottery is high: 99% of lottery winners and 96% of lottery losers enroll in their placement school.

[11]Table A.2 in Appendix A provides summary statistics of the characteristics used.

Figure 1. Predicted choice probabilities and ROL ranks per true ROL rank of schools and per switch status of students.



Note: The boxes cover the 25^{th}–75^{th} percentiles; the vertical lines cover the 5^{th}–95^{th} percentiles; the midline shows the group median. Displayed t-statistic refers to the difference in average choice probability at the top-ranked school for switchers and stayers.

that adding the social group and student characteristics yields modest improvements over the specification with only the predicted choice probability and school fixed effects.

Columns (4)–(6) of Table 5 look at subgroups of switches. Column (4) considers switches that co-occur with a residential move. The estimated coefficient on the predicted choice probability is more negative for these switches than for the full sample, which suggests that parents take their child's current school match into account when considering to move. Column (5) considers switches that co-occur with low academic performance. The estimated coefficient for these switches is closer to zero, implying that the student-school match has a weaker relationship with such switches. The final column excludes switches that co-occur with residential moves or low academic performance. The estimated coefficient is close to the one from the richest specification for all switches in column (3).

As robustness check, Table C.1 in Appendix C reports the estimates using the full sample

Table 5. Estimation results from logit model for school switching

Term	All switches	All switches	All switches	Switch + move	Switch + low perf.	Other switches
	(1)	(2)	(3)	(4)	(5)	(6)
Choice probability	-1.702^{***}	-2.290^{***}	-2.165^{***}	-3.388^{***}	-1.347^{***}	-2.205^{***}
	(0.161)	(0.170)	(0.172)	(0.650)	(0.288)	(0.208)
	[0.182]	[0.101]	[0.115]	[0.034]	[0.260]	[0.110]
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Group FE		Yes	Yes	Yes	Yes	Yes
Student char.			Yes	Yes	Yes	Yes
Accuracy	0.624	0.645	0.654	0.650	0.673	0.652
Sensitivity	0.595	0.614	0.627	0.671	0.650	0.636
Specificity	0.630	0.652	0.659	0.649	0.674	0.654
# of switches	5771	5771	5771	429	1827	3636
# of students	34599	34599	34599	34599	34599	34599

[a] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[b] Standard errors in parentheses; odd ratios in brackets. Accuracy: share of all students correctly predicted; sensitivity: share of switchers predicted as switchers; specificity: share of stayers predicted as stayers.

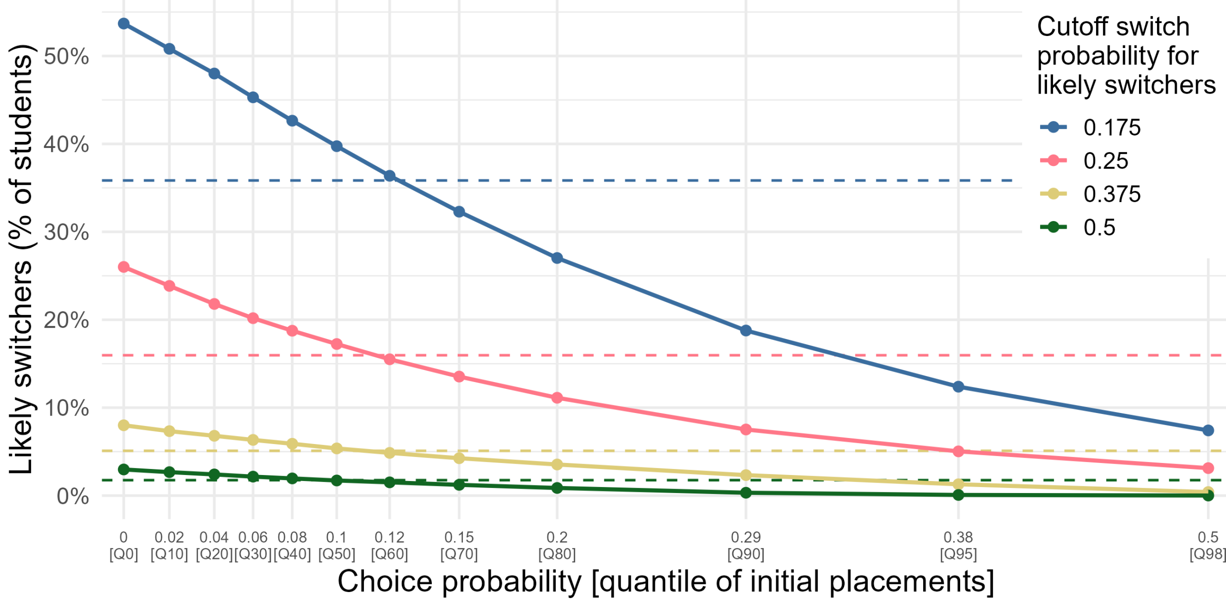
that includes the losers of the admission lotteries. The estimated coefficients on the predicted choice probabilities remain significantly negative and similar in size. The model has the same predictive power. Unsurprisingly, the estimation results also show that students who were not assigned to their first choice are more likely to switch schools than lottery winners.

Figure 2 illustrates the relationship between between school choice and switching. The figure shows the share of students that would be classified as likely switchers for different imputed choice probabilities, keeping all other characteristic constant. We consider different cutoff values in predicted switch probabilities to classify likely switchers. For example, for the cutoff of 0.25, the likely switchers are students with a predicted switch probability exceeding 0.25. With that cutoff, 17% of the students with the median predicted choice probability (Q50 on the x-axis) are likely switchers. If we change the choice probability to 0.02 (Q10), about 24% are classified as likely switchers. And if we increase the choice probability to 0.29 (Q90), only 8% are classified as likely switchers. The figure confirms that students with hard-to-rationalize initial school choices are substantially more likely to switch schools. This result implies that the initial school assignment can have a significant impact on subsequent switching behavior.

6. Policy implications

In this section, we evaluate the potential welfare effects of three different adjustments of the school assignment mechanism. The aim of these adjustments is to reduce school switching.

Figure 2. Predicted share of likely switchers at various imputed choice probabilities



Note: Dashed lines show the share of likely switchers under original choice probabilities.

We consider: (*i*) replacing the random lottery numbers with priorities based on predicted choice probabilities or predicted switch probabilities; (*ii*) removing schools with high predicted switch probabilities from students' ROLs; and (*iii*) replacing the school that switchers were initially assigned to with their eventual destination school.

Replacing random tie breakers with predicted choice probabilities or predicted switch probabilities gives priority to students on the basis of their fit with the rest of the student body or on the basis of the expected probability to stay at the school, respectively. Preventing students from enrolling in schools they are likely to leave can be interpreted as an upper bound estimate on the possible improvements from a personalized information treatment where students are advised against applying to schools that they are likely to leave. Replacing switch origin schools with switch destinations on the ROL is *ex ante* infeasible; we use it as a welfare-improving benchmark.

For the simulations, we follow De Groote (2025), who estimates the costs and benefits of counterfactual academic tracking policies in Belgian secondary schools. As a baseline, we replicate the initial allocation using the actual mechanism and lottery numbers.[12] For each adjustment, we simulate the DA mechanism separately by track level and cohort, using

[12]The simulated baseline allocation differs slightly from the actual allocation because we merge programs within the same track in a given school. This does not generate systematic differences in the allocation.

students' actual lottery numbers, and evaluate the resulting allocations.[13] In adjustment *(ii)*, if more than half of the schools on a student's ROL have a switch probability above our cutoff, we keep the 50% of schools with the lowest switch probability to ensure that all students still have enough options on their ROL. In adjustment *(iii)*, if a student switches to a school outside the Amsterdam school system, we treat the destination school as part of the initial lottery with unlimited capacity.

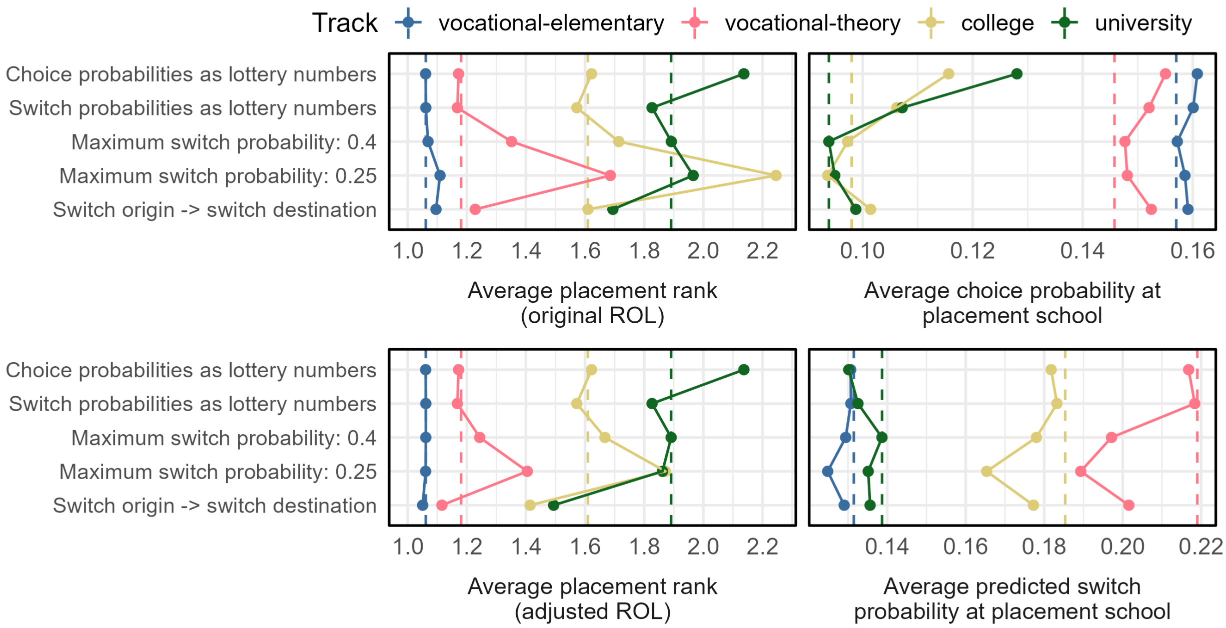
We measure the immediate result of an allocation by the average rank of the placement schools (both according to the original and modified ROLs where applicable). To quantify match quality and expected switching costs, we report the average predicted choice probability and the average predicted switch probability at the placement school. We also assess allocations in terms of the resulting segregation across schools along the dimensions of ethnicity, parental income, and academic achievement. We quantify segregation using the Gini coefficient, following Kim and Jargowsky (2009), who recommend this measure for continuous variables. For each dimension of segregation, we compute school-level aggregates (share of students with immigration background, average income, average primary school test score) and take the 0–1 rescaled sum of pairwise differences across schools. Higher values correspond to more segregation.

Figure 3 summarizes the results of the counterfactual allocations on four dimensions per track level. For comparison, the dashed lines show the original allocations by track. In the top-left panel we see that none of the counterfactual allocations lead to a substantial reduction of the average placement rank. The largest impact is from dropping schools where a student has a predicted switch probability exceeding 0.25: this policy increases (that is, worsens) the average placement rank by almost 0.5 in the college track, and 0.3 in the vocational-theory track. However, this result is a mechanical consequence of removing some top-ranked options from students' ROLs. The bottom-left panel removes this mechanical effect by using the adjusted ROL to calculate placement ranks. With this measure, much of the negative impact of the maximum switch probability adjustment disappears. Using predicted choice probabilities as priorities worsens the average placement rank in the university track. The reason is probably that similar students may now have priority at each others' top-ranked schools, thereby increasing competition for these spots. This pattern is similar to the difference between DA with multiple tie-breaking and DA with single tie-breaking. Replacing switch origin schools with switch destination schools is the only policy that consistently decreases average placement ranks. Because many switches are to schools with unfilled capacity, there is less competition for places at popular schools.

The top-right panel shows that as expected, using predicted choice probabilities as priorities increases the average predicted choice probability of placement schools. The increases are relatively large in the college track and the university track. Using predicted switch probabilities as priorities also increases the average predicted choice probabilities, but to a smaller

[13]In 2015 students had separate lottery numbers for each school. For that year we assign the lottery number of the switch origin to the switch destination; any remaining ties are broken randomly.

Figure 3. Simulated school assignment results



Note: Dashed lines show values under the original school assignments.
Unassigned students are imputed low choice probabilities, and high placement ranks and switch probabilities.

extent. No adjustment leads to a lower average choice probability in any track.

The bottom-right panel shows the the average predicted switch probabilities with the different allocations. For most students, predicted switch probabilities are reduced the most by removing high switch probability schools from their ROLs.[14] For students in the university track, the counterfactual where predicted choice probabilities are used as priorities reduces predicted switching the most.

We assess the social dimension of the counterfactual allocations by considering the resulting school segregation. Table 6 reports the Gini coefficients for between-school segregation in academic performance, ethnicity, and parental income. For comparison, the bottom two rows show the Gini coefficients of the actual school enrollments before and after switching.[15]

The only adjustment that has a notable impact on segregation is the replacement of switch

[14]Impacts with the 0.4 cutoff at the vocational-elementary and university track are small as there are hardly any schools with switch probabilities above the cutoff.

[15]The before switching coefficient is almost identical to the simulated version. Differences are due to our inability to account for special programs within schools, which slightly changes school capacities and ROLs.

Table 6. Between-school Gini coefficients under simulated school assignment mechanisms.

	Gini coefficient of segregation		
Simulated school assignment	Academic performance	Ethnicity	Income
Original school assignments	0.357	0.369	0.395
Choice probabilities as lottery numbers	0.358	0.298	0.412
Switch probabilities as lottery numbers	0.362	0.305	0.412
Maximum switch probability: 0.4	0.352	0.373	0.399
Maximum switch probability: 0.25	0.339	0.322	0.364
Switch origin → switch destination	0.188	0.429	0.207
Actual assignments: Before switching	0.354	0.357	0.386
Actual assignments: After switching	0.184	0.449	0.207

origins with switch destinations, which decreases segregation by academic performance and parental income, but increases segregation by ethnicity. The *Switch origin → switch destination* results are similar but not identical to the actual assignments after switching, as the former takes into account spillover effects, i.e., switchers who after the modification do not apply to popular schools leave open capacity which can be filled by other applicants. The simulations push similar students towards similar schools, yet we do not see notable increases in segregation. *Maximum switch probability* and *Switch origin → switch destination* disperse the student population better compared to the original assignments (especially the latter, which substantially expands the set of schools students enroll in). Some originally oversubscribed schools remain below capacity, while unpopular schools gain new students. This replacement of popular schools (generally associated with good test scores and high-income students) with less popular ones also explains why after switching, segregation by academic performance and by parental income decrease.

7. Conclusion

The school assignment literature is to a large extent based on the premise that students know how well each school in their choice set will suit them. Yet, a substantial share of students switch schools even when initially assigned to their most-preferred school. In this paper, we link initial school choices to subsequent school switching. First, we estimate school demand models to obtain predicted school choice probabilities. Low predicted choice probabilities at top-ranked schools constitute hard-to-rationalize choices, which we interpret as signals of potential application mistakes. We then show that students who choose and are placed in a school where their predicted school choice probability is low – that is, students who are likely to have made an application mistake –, are more likely to switch schools. Since not all poorly matched students will switch schools due to the presence of switching costs, we believe that the share of students making application mistakes exceeds the share of students switching schools.

Assuming that low predicted school choice probabilities and the resulting school switches indicate application mistakes, the assignment of students to schools can be improved by removing schools with a high predicted switch probability from students' ROLs. When implementing this adjustment within the DA mechanism, the adjustment preserves strategy-proofness.

Switch rates are highest in the two intermediate tracks (vocational-theory and college). These are also the tracks where switching can be reduced the most by the removal of high switch probability schools from ROLs: one in five or one in six switches can be avoided through this adjustment. Removing schools from students' ROLs is an intrusive intervention, but its effects can be seen upper bound of the improvements from better-informed school choices. Such information could be provided through automatic warnings about high predicted switch probabilities on the online platform where students submit their ROLs.

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Appendix A. Additional descriptive results

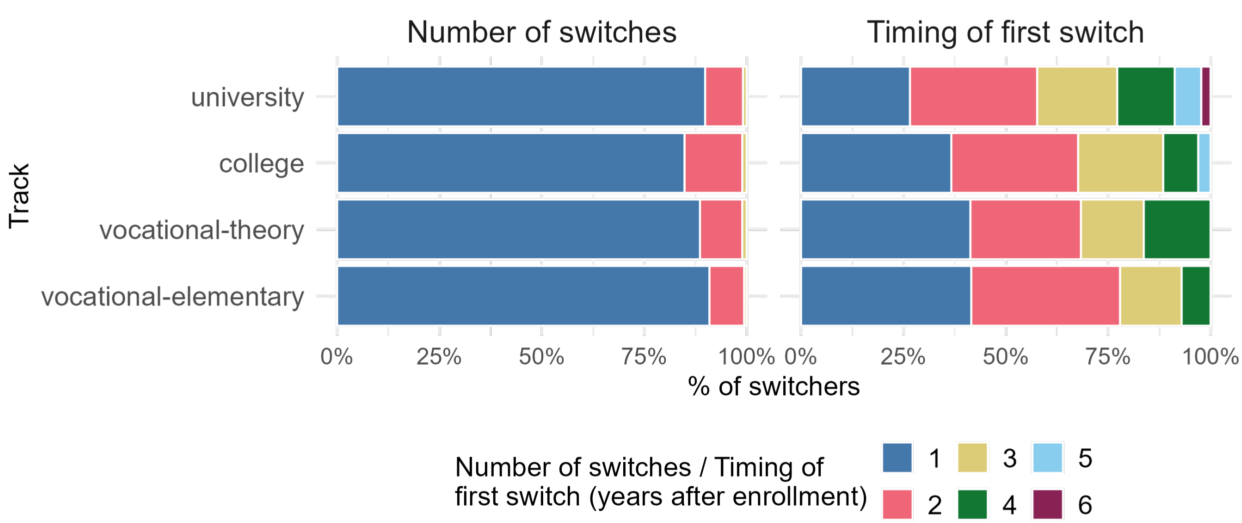
Table A.1 shows the school and match characteristics used in the school demand models. Table A.2 does the same for the student characteristics used when predicting school switching.

Table A.3 shows sample sizes per social group, defined by academic track, gender, and ethnicity. Our school demand models are fitted per social group (with student-school pairs as the unit of analysis), and some of the switch prediction models control for social group fixed effects (with students as the unit of analysis).

While students may switch schools more than once, our analysis considers only the first switch of each student, as future switches may be partially driven by confounders from the first switch. The left panel of Figure A.1 shows that this choice does not exclude many switches: across all track levels, 80% of switchers only switch once, and less than 2% switch more than twice.

Our analysis also excludes switches that the last few cohorts undertake in their last years, as data on student enrollments is available until 2023. However, the right panel of Figure A.1 shows that most switches occur in the first two years of secondary school, and data from those years is available for even the youngest cohorts in our sample. Extrapolating from this result, it is unlikely that many students in our data are currently misclassified as stayers because they switch only after our enrollment data end.

Figure A.1. Number of switches per student and timing of the first switch



Note: In the number of switches, 3 refers to 3 or more switches. In the timing of switches, for vocational tracks, 4 refers to 4 or more years, for the college track, 5 is 5 or more years, and for the university track, 6 is 6 or more years. These cutoffs reflect the expected time of completing each track.

Table A.1. School and match characteristics in the rank-ordered logit model. N = 1,305,781 student-school combinations, except for rank, which is missing for unranked schools. N_{rank} = 318,873.

Variable	Mean (SD)	Variable	Mean (SD)
rank on ROL	5.2 (3.3)	origin region missing * household income	0.013 (0.074)
school's lowest track offered	2 (0.87)	origin region missing * home-school distance	0.22 (1.6)
school's highest track offered	3.6 (0.85)	origin region missing * older sibling at school	0.00033 (0.018)
school size	0.72 (0.41)	household income * student's track is lowest offered	0.26 (0.34)
school's average end test score	-0.26 (0.82)	household income * student's track is highest offered	0.31 (0.39)
school's share of immigrants	0.62 (0.23)	household income * school size	0.47 (0.36)
school's share below median income	0.38 (0.15)	household income * school's share of immigrants	0.39 (0.22)
home-school distance	6.5 (5.2)	household income * Immigration background	0.39 (0.22)
older sibling at school	0.0094 (0.097)	household income * home-school distance	4.2 (4.2)
student's track is lowest offered	0.44 (0.5)	household income * older sibling at school	0.0063 (0.069)
student's track is highest offered	0.45 (0.5)	mother university education * student's track is lowest offered	0.13 (0.33)
end test score * school average end test score	0.43 (0.91)	father university education * student's track is lowest offered	0.1 (0.3)
end test score missing * school average end test score	-0.054 (0.37)	mother university education * student's track is highest offered	0.24 (0.42)
household income * school's share below median income	0.24 (0.13)	father university education * student's track is highest offered	0.2 (0.4)
end test score * student's track is lowest offered	-0.15 (0.66)	mother university education * school size	0.31 (0.46)
end test score * student's track is highest offered	0.24 (0.63)	father university education * school size	0.26 (0.44)
end test score * school size	0.17 (0.71)	mother university education * end test score	0.0097 (0.43)
end test score * school's share of immigrants	0.014 (0.63)	father university education * end test score	0.012 (0.39)
end test score * Immigration background	0.014 (0.63)	mother university education * school's share of immigrants	0.24 (0.32)
end test score * household income	-0.02 (0.41)	mother university education * Immigration background	0.24 (0.32)
end test score * home-school distance	0.49 (7.6)	father university education * school's share of immigrants	0.2 (0.31)
end test score * older sibling at school	0.0014 (0.091)	father university education * Immigration background	0.2 (0.31)
end test score missing * student's track is lowest offered	0.088 (0.28)	mother university education * household income	0.14 (0.19)
end test score missing * student's track is highest offered	0.088 (0.28)	father university education * household income	0.11 (0.18)
end test score missing * school size	0.14 (0.32)	mother university education * home-school distance	2.5 (4.6)
end test score missing * school's share of immigrants	0.12 (0.27)	father university education * home-school distance	2.1 (4.2)
end test score missing * Immigration background	0.12 (0.27)	mother university education * older sibling at school	0.0037 (0.061)
end test score missing * household income	0.073 (0.16)	father university education * older sibling at school	0.0033 (0.057)
end test score missing * home-school distance	1.3 (3.7)	mother education missing * student's track is lowest offered	0.09 (0.29)
end test score missing * older sibling at school	0.0023 (0.048)	father education missing * student's track is lowest offered	0.17 (0.37)
Western immigrant * student's track is lowest offered	0.085 (0.28)	mother education missing * student's track is highest offered	0.075 (0.26)
Western immigrant * student's track is highest offered	0.081 (0.27)	father education missing * student's track is highest offered	0.13 (0.34)
Western immigrant * school size	0.13 (0.33)	mother education missing * school size	0.13 (0.33)
Western immigrant * school's share of immigrants	0.12 (0.26)	father education missing * school size	0.23 (0.4)
Western immigrant * Immigration background	0.12 (0.26)	mother education missing * end test score	-0.065 (0.39)
Western immigrant * household income	0.072 (0.16)	father education missing * end test score	-0.13 (0.52)
Western immigrant * home-school distance	1.2 (3.3)	mother education missing * school's share of immigrants	0.12 (0.27)
Western immigrant * older sibling at school	0.0014 (0.037)	mother education missing * Immigration background	0.12 (0.27)
non-Western immigrant * student's track is lowest offered	0.19 (0.39)	father education missing * school's share of immigrants	0.21 (0.33)
non-Western immigrant * student's track is highest offered	0.13 (0.33)	father education missing * Immigration background	0.21 (0.33)
non-Western immigrant * school size	0.24 (0.41)	mother education missing * household income	0.074 (0.17)
non-Western immigrant * school's share of immigrants	0.23 (0.34)	father education missing * household income	0.13 (0.21)
non-Western immigrant * Immigration background	0.23 (0.34)	mother education missing * home-school distance	1.2 (3.5)
non-Western immigrant * household income	0.15 (0.21)	father education missing * home-school distance	2.2 (4.3)
non-Western immigrant * home-school distance	2.2 (3.8)	mother education missing * older sibling at school	0.0018 (0.043)
non-Western immigrant * older sibling at school	0.004 (0.063)	father education missing * older sibling at school	0.0029 (0.053)
origin region missing * student's track is lowest offered	0.014 (0.12)	(school's average end test score)^2	0.74 (1.1)
origin region missing * student's track is highest offered	0.017 (0.13)	(school's share of immigrants)^2	0.44 (0.29)
origin region missing * school size	0.026 (0.16)	(school's share below median income)^2	0.17 (0.12)
origin region missing * school's share of immigrants	0.022 (0.12)	(end test score * school average end test score)^2	1 (3)
origin region missing * Immigration background	0.022 (0.12)	(household income * school's share below median income)^2	0.074 (0.076)

Table A.2. Student characteristics in the switch regressions. $N = 34{,}599$ students.

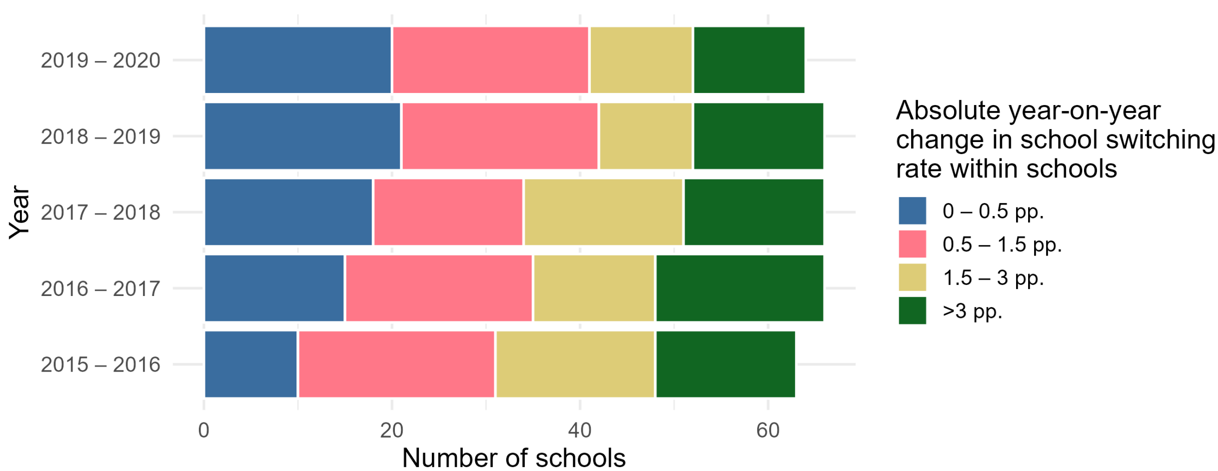
Variable	Mean (SD)
Choice probability	0.13 (0.12)
ROL length	7.2 (3.8)
track = college	0.27 (0.44)
track = vocational-theory	0.24 (0.43)
track = vocational-elementary	0.22 (0.42)
cohort	2018 (1.7)
end test score (standardized)	-0.074 (1)
end test score missing	0.19 (0.39)
first gen. immigrant	0.056 (0.23)
second gen. immigrant	0.55 (0.5)
Western immigrant	0.19 (0.39)
non-Western immigrant	0.38 (0.49)
household income (percentile)	0.62 (0.27)
mother university education	0.35 (0.48)
father university education	0.29 (0.45)
mother education missing	0.2 (0.4)
father education missing	0.35 (0.48)

When predicting the outcome of school switching, we use placement school fixed effects, assuming that within schools, switching rates are fairly constant over time. Figure A.2 shows that this assumption is plausible: the majority of schools experience minimal fluctuations in switching rates over years, with no clear linear trends of increasing/decreasing switching rates.

Table A.3. Number of students and student-school units per social group in the rank-ordered logit models.

Track	Gender	Ethnicity	# students	# student-school
vocational-elementary	female	immigrant	3381	68041
vocational-elementary	female	native	965	19492
vocational-elementary	male	immigrant	3468	69719
vocational-elementary	male	native	945	19059
vocational-theory	female	immigrant	3544	119399
vocational-theory	female	native	1603	53994
vocational-theory	male	immigrant	3367	113607
vocational-theory	male	native	1439	48382
college	female	immigrant	3454	108990
college	female	native	2911	91957
college	male	immigrant	3265	102898
college	male	native	2619	82569
university	female	immigrant	2485	85166
university	female	native	3423	117356
university	male	immigrant	2366	81497
university	male	native	3602	123655

Figure A.2. Magnitude of percentage point change in each school's switching rates compared to the previous year

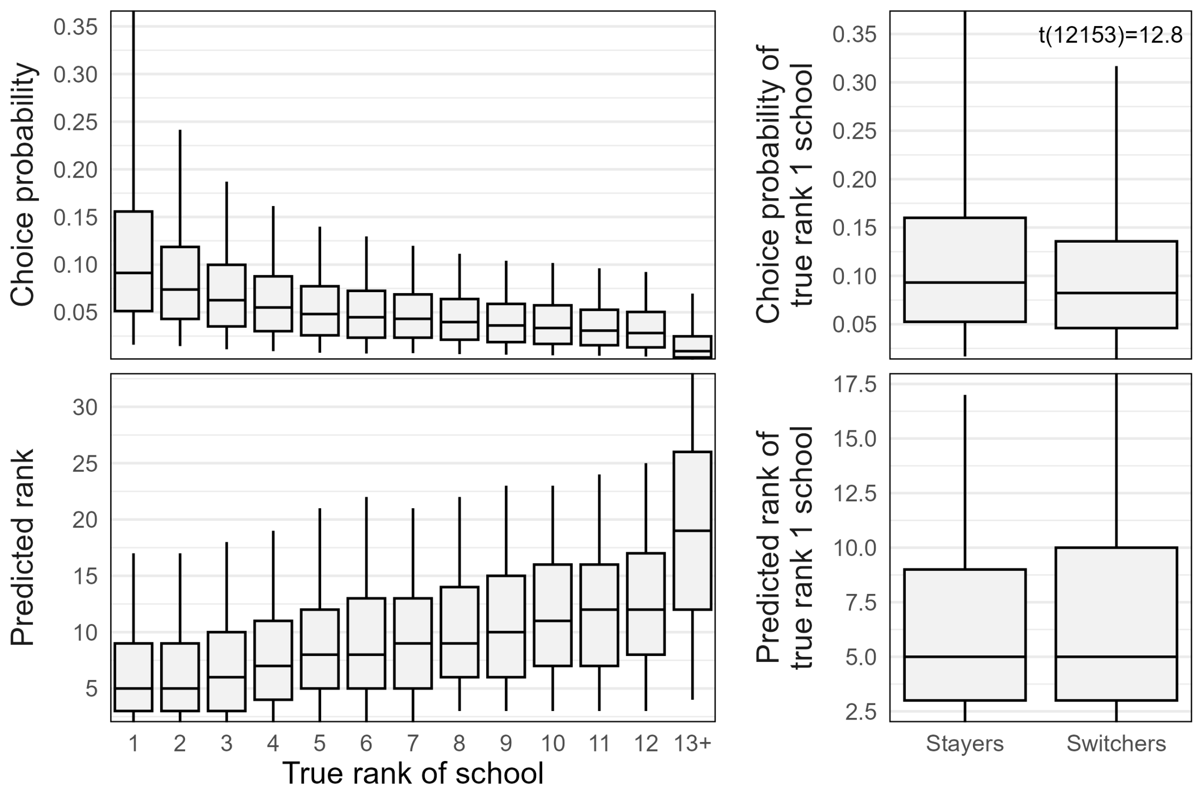


Note: Each school's switching rate is calculated for every year; the absolute difference of switching rates in consecutive years is shown, measured in percentage points. The number of schools varies due to school openings/mergers.

Appendix B. Alternative rank-ordered logit specification

Figure B.1 repeats the results from Figure 1, but using a vector of school characteristics S_j instead of school fixed effects ϕ_j (and the same match characteristics Z_{ij}). The results are slightly worse at identifying the students' preferred schools, but the predicted utilities are still moderately correlated with true preferences.

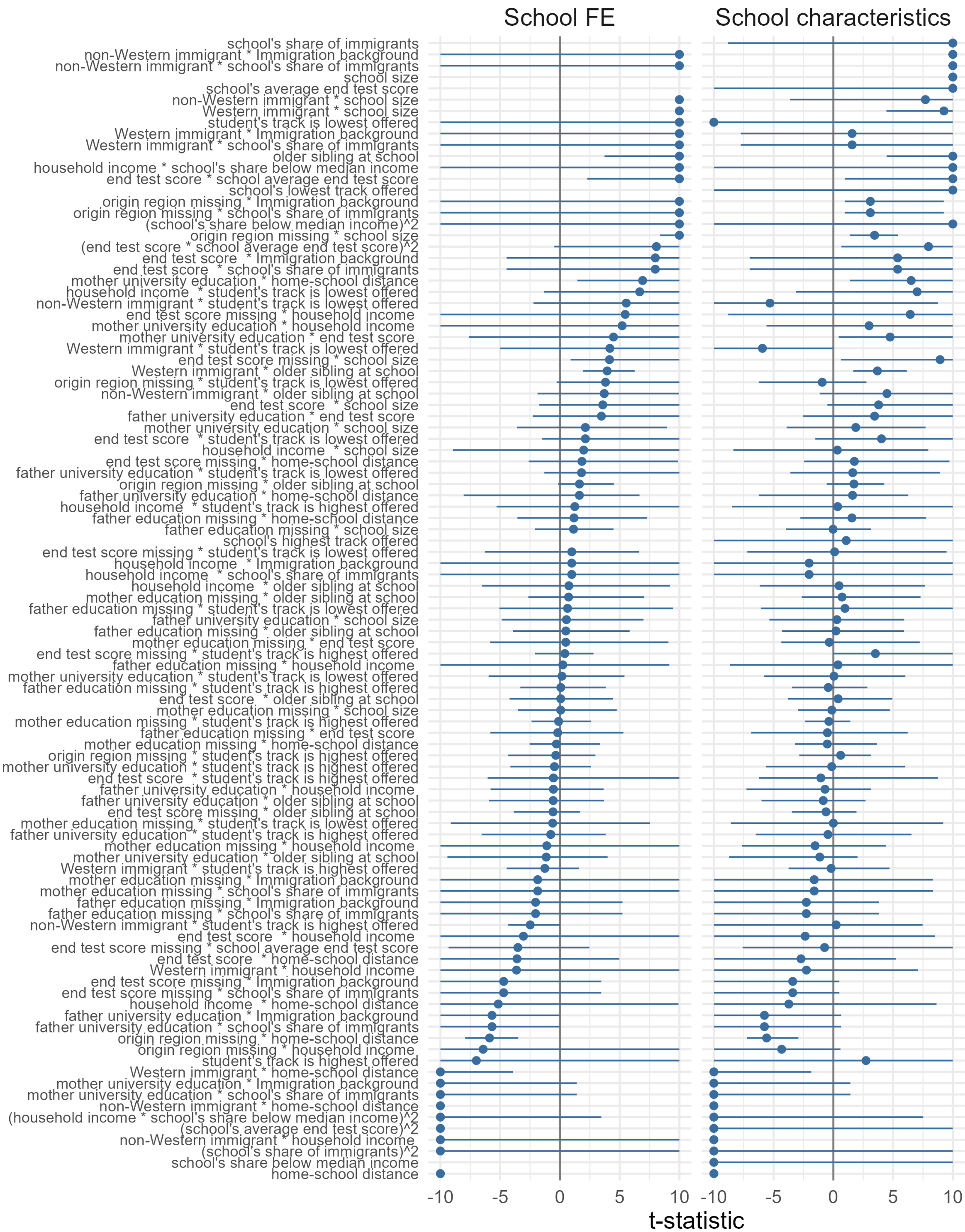
Figure B.1. Predicted choice probabilities and ROL ranks per true ROL rank of schools and per switch status of students using school characteristics



Note: The boxes cover the 25^{th}–75^{th} percentiles; the vertical lines cover the 5^{th}–95^{th} percentiles; the midline shows the group median. Displayed t-statistic refers to the difference in average choice probability at the top-ranked school for switchers and stayers.

Figure B.2 presents all rank-ordered logit coefficient estimates for the main model and the alternative specification with school charateristics, with each point in a row corresponding to the estimate for a different social group. The figure presents t-statistics instead of coefficient estimates to facilitate the comparison of effect sizes across variables.

Figure B.2. Estimated t-statistics for each independent variable for each rank-ordered logit specification and social group



Note: Points show the mean t-statistic across models; lines show the range. All coefficients are truncated at ± 10 for readability; the true range off t-statistics is $[-322; 275]$. Only the school FE models include placement school FE.

Appendix C. Robustness checks: switch prediction

While the majority of switches occur after enrollment, some students immediately enroll in a different school than their placement school. These immediate switches may be different than switches after enrollment: they are more likely to be driven by mistakes in the initial application, and as at the point of switching students do not yet know their classmates or teachers, there is less opportunity to learn about school quality. We repeat the analysis of predicting switching including these students who switch between the publication of lottery outcomes and initial enrollments (these non-compliers to the lottery were previously excluded from the analysis) to see whether our results are robust to the definition of school switching. We also expand the sample of students: we consider both lottery winners and lottery losers, and account for the higher average switch rate of lottery losers by including a dummy variable in the model to control for placement rank.

Table C.1 repeats the all-switches models shown in Table 5 using the expanded switch definition. Most results are similar as the findings in the main text: in the most complete model, a one percentage point increase in the choice probability of the placement school decreases subsequent switch probability by over 2%. The increased heterogeneity in switch types slightly reduces predictive power compared to the main model.

Table C.1. Estimation results from logit models for *any* school switching

	(1)	(2)	(3)
	−0.416***	−0.464***	−0.502***
Placement rank = 1	(0.033)	(0.034)	(0.034)
	[0.66]	[0.629]	[0.605]
	−1.824***	−2.448***	−2.394***
Choice probability	(0.141)	(0.149)	(0.15)
	[0.161]	[0.086]	[0.091]
School FE	Yes	Yes	Yes
Group FE		Yes	Yes
Student char.			Yes
Accuracy	0.624	0.636	0.638
Sensitivity	0.584	0.609	0.615
Specificity	0.635	0.643	0.644
# of switches	8968	8968	8968
# of students	42782	42782	42782

[a] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[b] Standard errors in parentheses; odd ratios in brackets. Accuracy: share of all students correctly predicted; sensitivity: share of switchers predicted as switchers; specificity: share of stayers predicted as stayers.