ARI Working Paper Series

No. 30 | March 2014

Academic Transfer, Self-Selection, and the Causal Effects

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Abstract

We investigate the type of self-selection arising in college transfer in Korea, and then estimate the returns to additional college education gained through transfers from two-year community colleges to four-year colleges. In this paper, we show that academic transfer is consistent with a positive selection hypothesis, in the sense that students with characteristics correlated positively to productivity are more likely to transfer to four-year colleges from community colleges. These empirical results also meet an underlying dispersion condition. In addition, we find that the transferred would make a statistically significant return to additional college education.

Keywords: College Transfer, Propensity Score Matching, Self-Selection
JEL Classification Numbers: A23, I29, J39

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I. Introduction

Since the 1960s, many studies have addressed estimating the economic returns to college education. The bulk of the studies argue that college education plays a crucial role in the labor market. Besides, some recent studies stress the importance of college transfer, as the fraction of transfer students turned out to be on the rise in the United States. However, little attention has been paid to examining the causal effects of college transfer. Of course, using panel data techniques, Hilmer (2002) finds that the quality of the universities attended before transferring should have positive effects on future earnings, as well as the quality of the universities from which a student graduated. Nonetheless, there have yet been few studies of estimating the causal effects of transfer.

In this paper, we consider the self-selection problem and the causal effects of college transfer, in particular the one from two-year community colleges to four-year colleges or universities. To do this, we incorporate the standard migration theory into an academic transfer model. Logically, the academic transfer seems similar to migration from underdeveloped regions to developed regions. Just as migration is primarily motivated by migrants' economic interests, those who seek upward academic transfer would also make this decision, as they are convinced that it will result in a rise in their income.[1]

More specifically, using the migration theories as developed by Borjas (1987) and Chiquiar and Hanson (2005), we address the self-selection problem in the college transfer setting and then estimate the labor market returns to additional college education by the transfer. To this

[1] There may be various motivations for upward transfer: students' expectation of an increased skill price in terms of observable socioeconomic background; self-recognition of their ability to produce more; the desire to acquire better jobs, change majors, apply for graduate schools, or enter schools of good reputation; and some other unobserved characteristics.

end, we analyze the type of selection characterizing college transfer by comparing the wage densities of non-transferred community college graduates, i.e., associate bachelor, (hereafter, the non-transferred) with those of four-year college graduates who transferred from community colleges (hereafter, the transferred) by means of this counterfactual concept.

For the counterfactual wage distribution, we obtain the wage distribution of the non-transferred matched to the transferred with propensity score matching (PSM). We then regard the wage distributions for the matched group as the counterfactual wage distribution of the transferred.[2] This comparison between the actual wage distribution of the non-transferred and the counterfactual wage distribution of the transferred enables us to see from which part of the overall wage distribution of community college graduates the transferred are selected.

With this counterfactual concept, we can also estimate the causal effects of academic transfer in terms of wage, i.e., starting salary in our case. In practice, it might be sufficient for estimating the causal effects to obtain a sample in which community college students are randomly transferred to four-year colleges. However, the problem is that it is impossible to guarantee the randomness, and thus we should acquire the counterfactual wages of the transferred, comparing them with their actual wages. For the causal effects of transfer (treatment), we have three key estimands: average treatment effect on the treated (*ATT*), average treatment effect on the controls (*ATC*), and average treatment effects (*ATE*).

This paper is organized as follows: the next section shows data sources and gives descriptive statistics regarding college transfers. Section III presents the theoretical foundation of self-selection and preliminary results of estimating propensity scores. Section IV identifies the type of self-selection and the causal effects of transfer. Section V concludes.

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[2] Note that the counterfactual wage distribution of the transferred refers to the wage distribution of the non-transferred adjusted to the covariates of the transferred.

II. Data and Summary Statistics

1. Data

In order to investigate the type of selection arising amongst transfer students from community colleges, we collected data from the *2005 Graduate Occupational Mobility Survey (GOMS)* conducted by the Korea Employment Information Service. The *GOMS* is the largest short-term panel survey of a representative sample of Korean college graduates. It is funded by the Employment Insurance Fund, sponsored by the Ministry of Labor, and officially approved by Statistics Korea. The *2005 GOMS* was launched in 2006 for a population of 502,764 college graduates, who graduated between August 2004 and February 2005, and was conducted annually until 2008. The first survey comprises 26,544 observations, that is, it covered approximately 5% of the target population. The dataset contains the graduates' demographic background, school life, job search, job training, preparation for jobs, and information on current and/or past jobs.[3]

Among these variables, we focus on an experience(s) of college transfer to four-year colleges or universities from community colleges and starting salaries after graduation, along with demographic background. Note that we do not include non-transferred graduates who had previously attended another school, but entered their current school as a freshman by retaking the College Scholastic Ability Test, a college entrance exam in Korea. Students who transferred into community colleges are excluded as well, as are those who transferred from four-year colleges. These two types of observations can be considered irrelevant, and not of

[3] Heckman, Ichimura, and Todd (1997) argue that much of the bias may be eliminated by the matching methods using comparison groups in the same labor market and the same questionnaire. Fortunately, as will be described below, our dataset used to calculate the transfer effects would most likely meet these conditions.

interest in our study, given our focus on examining the type of selection in community college transfers. We also exclude any graduates not responding to the question as to whether current job is their first job after college graduation, along with those not responding with their prior school information. Furthermore, only the graduates who are fully employed in their first job are included in our analysis. The fully employed workers are defined as those who have, by law, an employment contract for one year or more. These exclusions result in eliminating more than 11,000 observations from the original sample. However, note that the main purpose of the *GOMS* is to survey overall employment after college rather than to estimate the effects of transfer.

To identify types of selection in transfer and measure transfer effects immediately after college graduation, we use monthly starting salaries from the *GOMS* as the variable of interest. This variable also includes any daily or weekly starting salaries converted to a monthly basis by the *GOMS*. In fact, using the starting salaries would be more acceptable than using graduates' previous salaries, as their previous salaries cannot often capture the effects of transfer exactly, including the effects of experience after college graduation.

As demographic variables, we have the graduates' age and gender, their father's education, and the number of family members. Also included are the regions and type of high school they attended; in this paper, the sites are divided into four regions: Seoul, the other metropolitan cities, Kyeonggi Province, and the other provinces. High school location is used as a regional covariate because, in Korea, most high school students attend a hometown school. Finally, high schools are classified into two categories: academic and vocational.

2. Summary Statistics

As shown at the bottom of Table 1, we have 14,917 observations, among which the non-transferred (A) and college graduates in the non-transfer column amount to 5,841 and 8,467, respectively. The transferred (B) in the transfer column number only 609, i.e., 9.44% of those initially entering community colleges, $B/(A+B)$. The male-transferred number 246, and females, 363, as shown in the fifth column. The fraction of the transferred amongst females is higher by 2.17%p, compared to males, as in the eighth column.

We do not include graduates aged 21 and under in the analysis, as we have no transferred observations for the age group. In fact, it would be difficult for a graduate aged 21 or under to graduate from a four-year college following college transfer. This is because usually, though not necessarily, it would take at least two years to acquire the minimum qualifications to take

Table 1. Transfer and Non-Transfer Graduates by Covariates

Variable	Non-transfer				Transfer			
	Comm. col. graduates (A)		College graduates		College graduates (B)		Total	$\frac{B}{A+B}$
	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.	Freq.	Pct.
Gender								
Men	2,728	41.45	3,608	54.82	246	3.74	6,582	8.27
Women	3,113	37.35	4,859	58.30	363	4.36	8,335	10.44
Age								
20-21	209	100.00	0	0.00	0	0.00	209	0.00
22-23	1,702	82.86	349	16.99	3	0.15	2,054	0.18
24-25	1,788	37.11	2,945	61.12	85	1.76	4,818	4.54
26-27	1,072	25.41	3,015	71.46	132	3.13	4,219	10.96
28-29	247	10.50	1,928	81.97	177	7.53	2,352	41.75
30-31	146	41.13	136	38.31	73	20.56	355	33.33
32 and over	677	74.40	94	10.33	139	15.27	910	17.03
Father's education								
No schoolings	115	64.25	58	32.40	6	3.35	179	4.96
Elementary schools	1,137	52.93	881	41.01	130	6.05	2,148	10.26
Middle schools	1,395	50.84	1,219	44.42	130	4.74	2,744	8.52
High schools	2,521	40.70	3,446	55.63	227	3.66	6,194	8.26
Community colleges	131	33.16	255	64.56	9	2.28	395	6.43
Colleges	458	18.42	1,944	78.20	84	3.38	2,486	15.50
Graduate schools	84	10.89	664	86.12	23	2.98	771	21.50

<u>Location of high schools</u>								
Seoul	1,298	35.95	2,190	60.65	123	3.41	3,611	8.66
Other big cities	1,692	38.21	2,537	57.29	199	4.49	4,428	10.52
Kyeonggi Province	976	46.77	1,056	50.60	55	2.64	2,087	5.33
Other provinces	1,875	39.14	2,684	56.02	232	4.84	4,791	11.01
<u>Type of high schools</u>								
Academic high school	2,971	25.89	8,056	70.21	447	3.90	11,474	13.08
Vocational high school	2,870	83.36	411	11.94	162	4.71	3,443	5.34
Total	5,841	39.16	8,467	56.76	609	4.08	14,917	9.44

Source: *2005 Graduate Occupational Mobility Survey (GOMS),* Korea Employment Information Service

the entrance exams for transfer, aside from the additional years spent in four-year colleges. In practice, these graduates are likely to be some time away from transfer decisions. We also exclude graduates aged 32 and over from the analysis; it is likely that for older graduates, their experience effects would already have been reflected in their starting salaries after graduation, as mentioned before. Moreover, as will be shown later, it appears to be better balanced to focus on a cohort of graduates aged 22-31.

Table 1 also shows how father’s education and high school type are related to transfer rates. The seventh column shows that there are 6,194 graduates having fathers with a high school diploma, accounting for approximately 41.52% of the sample, and then middle school and college educated cases follow in turn. Overall, we can observe that transfer rates are positively related to father’s education. In particular, as shown in the eighth column, there exists a jump of more than 9%p in the transfer rates for graduates whose fathers have college degrees. Moreover, the transfer rate for those whose fathers have master’s or doctorate degrees is 21.50%. This suggests that community college students with highly educated families are more likely to transfer to four-year colleges, compared to those with primary or secondary school educated families. Whether it is coercive or self-directed, community college students appear to consider college transfer more frequently when well-educated family members' advice on transfer is available.

Regarding high school type, the college graduates from academic high schools in the non-transfer column number 8,056, accounting for 70.21% of the sample. In contrast, the number from vocational high schools is only 411 for the same case. The college transfer rate for graduates from academic high schools is also higher than for vocational graduates by 7.74%p, as shown in the eighth column. The high school locations do not show striking features in relation to transfer rates, though there is a noticeably low transfer rate in Kyeonggi Province.

III. Theoretical Background and Propensity Score Matching

1. Conceptual Framework

To develop an academic transfer model that addresses the self-selection problem, we follow Borjas' (1987) and Chiquiar and Hanson's (2005) approaches. While not identical to it, their basic model can be described by:

$$\ln w_{cc}^{i} = \mu_{cc}^{i} + \epsilon_{c}^{i}, \tag{1}$$

$$\ln w_{cu}^{j} = \mu_{cu}^{j} + \gamma^{j} + \epsilon_{c}^{j}, \tag{2}$$

where ϵ_c^i and $\epsilon_c^j \sim N(0, \sigma_c^2)$.[4] Assume that the error terms are independent for individuals i and j. Let w_{cc} and w_{cu} denote the wages of the non-transferred and the transferred,

[4] Note that the error terms ϵ_c^i and ϵ_c^j are assumed to be identically distributed because propensity score matching is based on the conditional independence assumption (CIA) as will be explained later. If their distributions were not identical, then the CIA would not be met. This implies that given the observable covariates, transfer decisions are non-random with regard to unobserved characteristics.

respectively, of all students who initially entered community colleges. For simplicity, the superscripts for individuals i and j are suppressed. In addition, let μ_{cc} and μ_{cu} denote the observable socioeconomic variables that affect wage levels for each group, i.e., base wages. Specifically, μ_{cu} is the base wage of the transferred, reflecting a counterfactual wage that they would expect to earn if they had graduated from community colleges. Consequently, γ represents the wage premium obtained from additional college education through transferring to four-year colleges.

In making transfer decisions, community college students would probably transfer to four-year colleges or universities if they expect that the rise in their lifetime income, in the labor market after graduation because of the transfer, is greater than its costs (strictly in present value). The transfer decision of community college students can be expressed approximately as below:

$$\ln w_{cu} > \ln w_{cc} + TC,$$

where TC denotes transfer costs, that is, the opportunity costs of additional years at college and the costs of transfer preparation.[5]

In this respect, Borjas (1987) argues that the negative-selection (positive-selection) hypothesis implies that when income dispersion in the country of origin is greater (smaller) than in the country of destination, the less (more) skilled are more likely to migrate from the

[5] In practice, it is common in Korea that the students who intend to transfer to another college go to related private educational institutes because unlike the United States, the students generally take an entrance exam when hoping to transfer. Of course, TC also includes the time costs to prepare for it.

country of origin. The underlying meaning of these hypotheses is that assuming higher income dispersion in the country of origin, with the same measured skills, low-income workers would have more incentive to migrate than high-income workers, as they can probably find opportunities to increase their income, owing to the smaller income dispersion in the country of destination. In this case, the immigrants are “negatively selected” from the population of the original country.

For the college transfer selection problem, whether the transfer selection is positive or negative could depend on the difference between within-group wage dispersions (e.g., σ_c^2 and σ_u^2) for individuals with comparable attributes. Note that σ_u^2 is the within-group wage dispersion of *non-transferred college graduates*. Recall that σ_c^2 is, by definition, the within-group wage dispersion of both the transferred and the non-transferred who attended community colleges. For example, aside from the transfer effects, γ, if $\sigma_c^2 < \sigma_u^2$, then community college students with high productivity will have a greater incentive to transfer than otherwise. In practice, assuming that the transferred have the same productivity as the *non-transferred college graduates* at the mean of the wage distribution, highly-productive community college students would intend to transfer, as they could boost their income owing to the greater within-group wage differentials. On the contrary, if $\sigma_c^2 > \sigma_u^2$, less productive community college students would have a greater incentive to transfer than those with high productivity. The former, in our case, can be termed positive selection, while the latter, negative selection. In relation to this, we investigate the empirical results relating to the difference between σ_c^2 and σ_u^2, and which type of selection of the transferred they are consistent with, by comparing the counterfactual wage distribution of the transferred with the actual distribution of the non-transferred.

2. Propensity Score Matching

To examine the type of selection involved in transfer, we should obtain the counterfactual wage distribution of the transferred. To do so, we need to match the transferred and the non-transferred properly, in terms of observed covariates. In this regard, Rosenbaum and Rubin (1983) suggest that the balancing score (i.e., propensity score) is sufficient to remove bias from observed covariates through adjusting only for the difference in propensity score. One of the advantages of using the PSM is its ability to avoid the curse of dimensionality when the treated units (i.e., the transferred) are matched to the control units (i.e., the non-transferred) with many covariates. All the information about the characteristics of the treated and the control units can be incorporated by a single index, propensity score.

The propensity score can have various forms such as a probability, an odds ratio, or other indices for participating in a program. Among them, given the covariates of the transferred and non-transferred, the most popular method is to use logit or probit analysis to acquire the propensity scores. However, note that specifying empirical models for the propensity scores is not done to find covariates determining transfer decisions. Rather, it is simply done to set up covariates to obtain propensity scores so that we can match the treated and control units properly. In addition, too many covariates should not be included in the model because of the over-specification problem resulting in higher standard errors in the estimated propensity score.

With respect to the PSM, we have two important underlying assumptions satisfied: the conditional independence assumption (CIA) and a sizable overlap condition.[6] Rosenbaum and Rubin (1983) show that under the CIA, just as matching is valid on the covariates,

[6] For details, see Rosenbaum and Rubin (1983), Heckman, Ichimura, Smith, and Todd (1996), Heckman, Ichimura, and Todd (1997).

matching on the propensity score, a scalar function of the covariates, is also justified. The authors also argue that the treatment effect estimator, which adjusts for the propensity score, can be efficient and consistent. On the other hand, the overlap condition states that in order for propensity score matching to be valid, there must be a substantial overlap in the propensity score of the treated and the control units.

With our dataset, we estimate the propensity scores of transfer—predicted probabilities of transfer to four-year colleges—using logit regression analysis, one of the most frequently used statistical procedures. To specify a logit model for transfer (T_i), which is binary, we use as covariates the graduates' age (Age_i), their gender ($Gender_i$), their father's education ($FEdu_i$), the number of family members ($NumFam_i$), and dummies of the region and type of high school they graduated from.

$$\begin{aligned}\hat{T}_i = &-\underset{(.81)}{20.41^{***}} + \underset{(.03)}{.70^{***}} Age_i - \underset{(.13)}{1.18^{***}} Gender_i + \underset{(.05)}{.25^{***}} FEdu_i - \underset{(.04)}{.04} NumFam_i \\ &+ \underset{(.15)}{.63^{***}} OthCities_i - \underset{(.21)}{.31} Kyeonggi_i + \underset{(.16)}{.58^{***}} OthProvinces_i - \underset{(.13)}{1.54^{***}} VocSchool_i,^{7} \quad (3)\end{aligned}$$

Equation (3) shows the empirical results of the logit analysis, leading to predict the probability of transfer. Specifically, the probability of transfer to four-year colleges on average increases with age. It is also statistically significant that the more schooling a graduate's father received, the higher their transfer probability. Community college students from big cities and provinces are more inclined to transfer, and so are those who graduated

[7] For details, see the appendix. The figures in parentheses are corrected standard errors, and ***, **, and * indicate significance at a 1%, 5%, and 10% levels, respectively.

from academic high schools. However, recall that this specification is not designed to determine transfer models (Khandker et al. 2010), but simply to acquire propensity scores, indexed by multiple covariates, to enable matching.

To make the matching estimator effective, the transferred and the non-transferred matched need to be similar in terms of their observed covariates. To enhance the validity of the matching estimators, only the transferred and the non-transferred within the region of common support are included in the analysis as well. Then balancing tests are conducted, specifically, tests to check if the distributions of the covariates included in the model differ systematically between the two groups.

There are the various matching criteria, based upon the estimated propensity score, which can be used in these matching procedures. For our matching analysis, we adopt the single nearest-neighbor, caliper, kernel, and local linear matching methods among the criteria. Single nearest-neighbor matching, for instance, involves a non-transfer graduate being matched to its nearest neighbor in terms of their propensity scores for transfer.

IV. Self-Selection and Causal Effects of Transfer

1. Existence of Self-Selection in Transfer

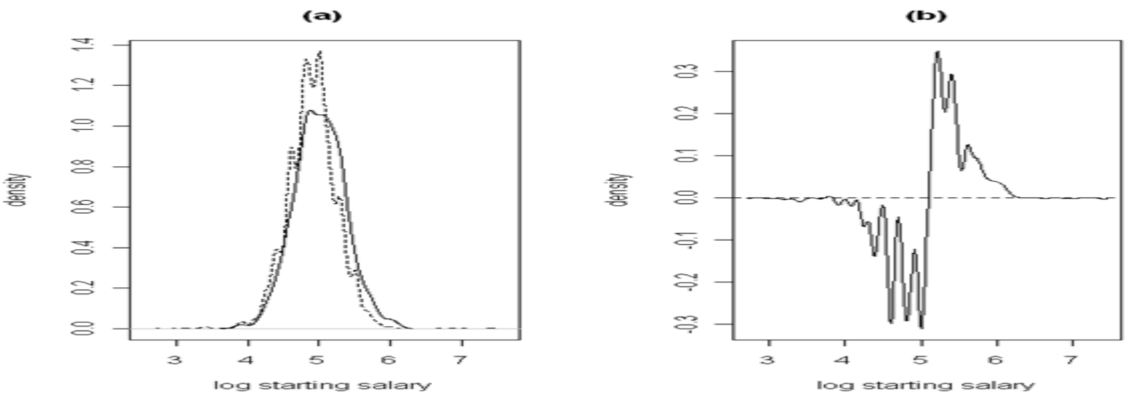
Conceptually, removing the wage premium to college transfer, γ, from Equation (2), enables us to obtain the counterfactual wage distribution of the transferred:

$$\ln w'_{cu} = \mu_{cu} + \epsilon_c. \tag{4}$$

By comparing the wage distributions in Equations (1) and (4), we can identify the type of selection arising in transfer. No differences between these two distributions would imply that the transferred are randomly selected from the population of community college students, in terms of observed as well as unobserved characteristics.

Using the single nearest-neighbor matching, we can compare the counterfactual log starting salary density of the transferred with the actual density of the non-transferred in Figure 1. At a glance, the counterfactual distribution of the transferred looks similar to the actual distribution of the non-transferred. Nonetheless, we can observe that it is likely that the transferred are selected non-randomly from the population of community college students, in relation to observable characteristics, owing to the difference between the two distributions in the figure. Specifically, the figure shows that the difference in log starting salary densities is

Figure 1. Comparison of Actual for the Non-Transferred and Counterfactual for the Transferred



Notes: Figure 1(a) shows the densities of the actual (the non-transferred, the dashed line) and the counterfactual (the transferred, the solid line) log starting salaries. Figure 1(b) shows the difference between the two densities in Figure 1(a).

negative in the lower tail, and positive in the upper tail, implying that there is a positive selection occurring in the transfer from community colleges.

Table 2 provides us with summary statistics for the log starting salary distributions. The means of the actual log starting salaries of the transferred and college graduates are both greater than that of the non-transferred (community college graduates). Specifically, the summary statistics demonstrate that the sample mean of college graduates' starting salaries is 30.59% ($=\{\exp(5.1771) / \exp(4.9102) - 1\} \times 100$) higher than that of the non-transferred. Additionally, the mean starting salary of the transferred is higher by 19.03%.

The within-group dispersions of starting salaries are greater for college graduates as well. Considering the relationship between the type of selection in transfer and the within-group wage dispersions suggested in the previous section, these statistics are consistent with the positive selection hypothesis in transfer, as shown in Figure 1.

This suggests that community college students who have observable characteristics that lead to having high productivity are more likely to transfer to four-year colleges or

Table 2. Starting Salary Distributions for Transfer and Non-Transfer Graduates

Log salary distribution	Actual for the non-transferred (community college graduates)			Actual for college graduates		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Non-transfer	4.9102	0.3419	4,955	5.1771	0.3917	8,373
Log salary distribution	**Counterfactual for the transferred**			**Actual for the transferred**		
	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Transfer	5.0085 (5.0118)	0.3524 (0.3514)	470	5.0585 (5.0844)	0.3901 (0.3808)	470

Notes: The sampling weights are applied to the actual and counterfactual log starting salaries for the transferred. However, no sampling weights are applied to those in parentheses.

Source: *2005 Graduate Occupational Mobility Survey (GOMS)*, Korea Employment Information Service

universities. Furthermore, these log starting salary differentials between groups are all statistically significant, although the sampling weights are not applied to test them.[8] The variances of the log starting salaries of the transferred and college graduates are statistically different from that of the non-transferred; meanwhile the variance of the transferred is not statistically different from the variance of college graduates. The variance of the counterfactual starting salaries of the transferred is also not statistically different from the variance of the actual starting salaries of the non-transferred. To sum up, all these statistics are consistent with the theoretical models supporting the positive selection hypothesis in transfer.

2. Causal Effects of Transfer

With data from the *2005 GOMS*, Figure 2 shows the actual and counterfactual log monthly starting salaries of the transferred, using single nearest-neighbor matching.[9] In this figure, we can observe the average transfer effect as the mean difference between the two distributions. With regard to these densities, Figure 2(b) presents the actual minus counterfactual density of the transferred. The density difference is negative from the left tail to a salary slightly over 5.0, and positive above this point. Evidently, returns to additional education through transfer do exist, as in Table 2.

By comparing the actual and counterfactual starting salaries of the transferred with no

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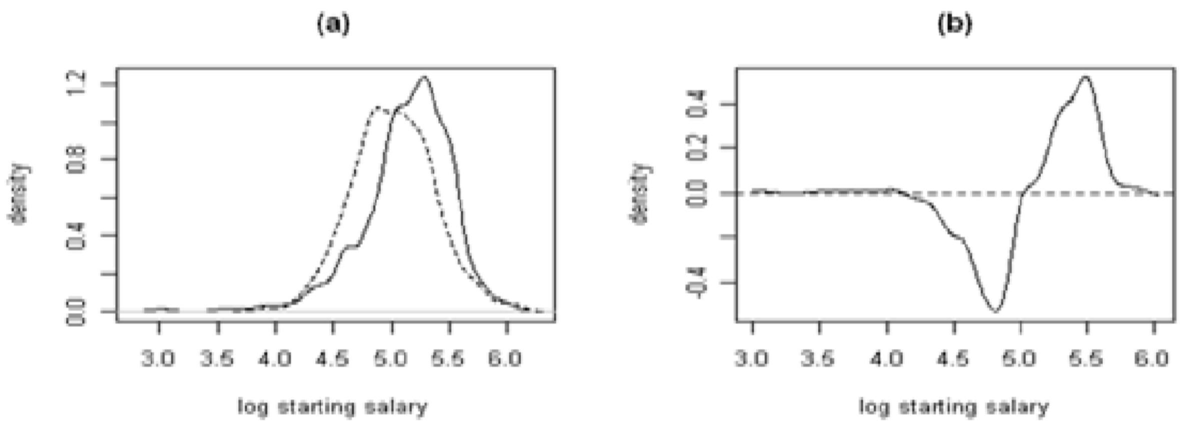
8 For want of space, the test results such as t-tests and variance ratio tests are not reported in this article, but can be provided upon request.

9 To evaluate the quality of the single nearest-neighbor matching, we conduct balancing tests. Overall, it appears that the matching method reduces the covariate imbalance considerably. The matched variables appear to be relatively well balanced for all and for male graduates, respectively. On the other hand, the observations on female graduates do not work as well in the balancing test, particularly because of an imbalance in age. For details, see Table A2 in the appendix.

sampling weights, we can confirm that there is a transfer effect of approximately 7.53% $(= \{\exp(5.0844) / \exp(5.0118) - 1\} \times 100)$ in Table 2; this result is similar to the average transfer effect on the transferred from the single nearest-neighbor matching in Table 3.

Using various matching methods with these estimated propensity scores ($\hat{T}_i$), we calculate a non-parametrically average treatment effect on the treated (ATT). In our case, the ATT from transfer is the mean difference between the log starting salaries of the transferred and the matched non-transferred, counterfactuals. On the other hand, the ATC (average treatment effect on the control units) indicates the mean difference between the log starting salaries of the matched transferred and the non-transferred; in this case, the former are counterfactuals. Consequently, the ATE (average treatment effect) is a weighted average of the ATT and ATC. Imbens (2003) and Heckman et al. (1998) argue that the treatment effect on the subpopulation of the treated units (ATT) is occasionally more meaningful than that on the whole population, i.e., the average treatment effect (ATE). In this respect, when we evaluate the importance of narrowly aimed programs, it may be irrelevant to consider even the potential treatment effects on the control units.

Figure 2. Comparison of Actual and Counterfactual for the Transferred



Notes: Figure 2(a) shows the densities of the actual (the solid line) and counterfactual (the dashed line) log starting salaries for the transferred. Figure 2(b) shows the difference between the two densities in Figure 2(a)**.**

Table 3. Causal Effects of Transfer by Matching Methods

Matching		NN	Caliper	Kernel	LLM
ATT		0.0713**	0.0725***	0.0468**	0.0404*
		[2.28]	[2.59]	[2.39]	[1.65]
ATC		0.0436	0.0436	0.0605**	0.0545
		[0.92]	[1.17]	[2.02]	[1.62]
ATE		0.0469	0.0470	0.0589**	0.0528*
		[1.16]	[1.14]	[2.17]	[1.87]
Common support	Untreated	3,516	3,516	3,516	3,516
	Treated	470	460	470	470
	Total	3,986	3,976	3,986	3,986

Notes: The figures in brackets indicate z-statistics from bootstrapping. There are 50 bootstrap replications. The nearest-neighbor matching is one-to-one. In addition, the tolerance of caliper is 0.01 in terms of propensity score, and the kernel functions used in kernel and local linear matching are Epanechnikov and tricube. ***, **, and * indicate significance at a 1%, 5%, and 10% levels, respectively. We confirm that, for all graduates, for example, our single nearest-neighbor matching reduces the covariate imbalance considerably, leading to the absence of significant differences in the covariates between the treated and control units. For details, see the appendix. On the other hand, we have a small pool of the transferred to be matched to the non-transferred, a weak common support problem in the community college graduates' place, and so perhaps it would be difficult to evaluate the estimates of ATC and ATE correctly.

Table 3 shows the average transfer effects on the transferred, which amount to approximately 4-7% of a monthly starting salary. This implies that the transferred would make a statistically significant return to additional college education of 4-7%. In contrast, most of the average transfer effects on the non-transferred and on all community college entrants do not significantly differ from zero.

V. Concluding Remarks

In this paper, we have attempted to answer the questions of which type of students transfer from two-year community colleges to four-year colleges or universities, and then to estimate the returns from additional college education gained through transfer.

Our findings are that there appears to be positive selection in college transfer, at least in Korea. This implies a non-random selection of students for college transfer, in terms of observable characteristics. In addition, the dispersion story also applies to this positive selection, as in Borjas (1987). Furthermore, we find that there exist causal transfer effects of 4-7%, through the various matching methods.

Ideally, it may be more interesting to estimate how the causal effects of transfer are in other countries, compared to Korea, along with the types of self-selection. However, we seldom find any other studies addressing the transfer effects in the literature. Hence, we hope that much future research is done on academic transfer in other countries, and that the transfer effects are directly comparable with those in Korea.

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Appendix

Table A1. Estimation Results from Logit Analysis

Transfer	All	Men	Women
Age	0.6985***	0.7640***	0.6933***
	(0.0278)	(0.0408)	(0.0411)
Gender	-1.1822***	--	--
	(0.1286)	--	--
Father's education	0.2527***	0.1209**	0.4222***
	(0.0459)	(0.0626)	(0.0701)
Number of family members	-0.0431	-0.0921*	0.0032
	(0.0434)	(0.0588)	(0.0673)
Other big cities	0.6333***	0.6399***	0.4735**
	(0.1566)	(0.2087)	(0.2461)
Kyeonggi province	-0.3096*	-0.8386***	0.0099
	(0.2150)	(0.3285)	(0.2948)
Other provinces	0.5782***	0.4878**	0.5809***
	(0.1614)	(0.2195)	(0.2409)
Vocational high school	-1.5353***	-1.2324***	-2.0445***
	(0.1348)	(0.1691)	(0.2382)
Constant	-20.4107***	-22.8019***	-20.9768***
	(0.8066)	(1.2195)	(1.1939)
Pseudo R^2	0.3066	0.3123	0.3279
Observations	5,425	2,895	2,530

Notes: The figures in parentheses are corrected standard errors, and ***, **, and * represent significance at a 1%, 5%, and 10% levels, respectively. Note that the purpose of specifying models to obtain propensity scores is not to obtain determinants models, but only to match properly the treated and control units with their covariates.

Table A2. Balancing Tests

Variables	Sample	All		Men		Women	
		t-stat.	p-value	t-stat.	p-value	t-stat.	p-value
Age	Unmatched	29.12	0.000	26.13	0.000	21.93	0.000
	Matched	-0.61	0.543	-0.35	0.729	-2.37	0.018
Gender	Unmatched	1.66	0.096	--	--	--	--
	Matched	0.46	0.646	--	--	--	--
Father's education	Unmatched	4.37	0.000	1.27	0.203	5.67	0.000
	Matched	0.21	0.835	-0.13	0.895	1.90	0.058
Number of family members	Unmatched	-4.33	0.000	-3.22	0.001	-2.50	0.013
	Matched	-0.02	0.981	0.30	0.768	-0.76	0.450
Other big cities	Unmatched	1.59	0.111	1.93	0.054	0.00	0.996
	Matched	-0.89	0.372	-0.53	0.595	0.69	0.493
Kyeonggi Province	Unmatched	-4.40	0.000	-4.19	0.000	-1.89	0.059
	Matched	-0.33	0.741	0.36	0.716	1.60	0.111
Other provinces	Unmatched	2.49	0.013	2.06	0.040	1.49	0.136
	Matched	0.20	0.838	-0.63	0.529	-0.61	0.539
Vocational high school	Unmatched	-9.72	0.000	-7.92	0.000	-6.09	0.000
	Matched	-1.81	0.071	-1.48	0.140	-3.04	0.003
Variables	Sample	All		Men		Women	
		LR χ^2	p-value	LR χ^2	p-value	LR χ^2	p-value
All covariates	Unmatched	1013.55	0.000	581.47	0.000	469.23	0.000
	Matched	5.35	0.720	4.27	0.749	19.83	0.006

Notes: Overall, we confirm that our single nearest-neighbor matching reduces the covariate imbalance considerably. For all and for men, the matched variables appear to be relatively well balanced. However, for women, good performance is not shown in the balancing test.