Title

Education, Job Requirements, and Commuting: An Analysis of Network Flows

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Education, Job Requirements, and Commuting: An Analysis of Network Flows

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Introduction

By now measures of employment "access" and "potential" have been widely diffused in the literature on regional economics and transport planning. Pooler (1995) gives a brief review of accessibility measures, indicating that these concepts date back to the 1930s. According to standard economic intuition, the employment access of a residential area increases with its proximity to concentrations of employment opportunities. The various indices of accessibility which have been proposed merely formalize and quantify this notion.

In this paper, we incorporate the spatial distribution of the demand for educational qualifications and the spatial distribution of the supply of educated workers into this framework. We ask:

1. How *different* are the computed measures of employment access and potential when variations in the spatial pattern of the demand for educated workers are recognized?

2. How *important* is the spatial pattern of the demand for educated workers in explaining variations in employment access and potential?

Following this introduction, we estimate models of employment access separately based upon workers of differing educational qualifications. These results allows us to investigate directly:

3. How *different* is the worktrip and residential location behavior of households of differing educational qualifications?

One reason for addressing these questions is that the knowledge-orientation of society will change the educational profile of the population. There are also reasons to believe that people with high education can choose their working time more freely than those with low education. It is also reported that the possibilities for telecommuting are positively related to the educational level. A more concrete reason is that the results of earlier work (Quigley and Hårsman, 1995) suggested that the travel patterns differ between workers in different industries and with different levels of education.

This empirical analysis is based upon the worktrip behavior of commuters in metropolitan Stockholm, disaggregated into three educational categories. The analysis is undertaken using gravity models of worktrip behavior and employment potential. We also conduct the analysis using more sophisticated models of worktrip behavior, namely the Poisson and the negative binomial relationships. Section II presents the methodology. The statistical results and their interpretation are in Section III.

Spatial Access

The most widely used empirical model of the accessibility of particular residential locations is based upon the gravity concept:

$$T_{ij} = \alpha R_i^{\beta} W_j^{\gamma} / d_{ij}^{\delta} , \qquad (1)$$

where Greek letters denote parameters.

The data used to estimate equation (1) consist of the matrix of commute flows T_{ij} between origin zones i and destination zones j and the distance or travel times d_{ij} between them. From the elements of the matrix, the number of workers resident in each zone (R_i) can be estimated ($R_i = \sum_j T_{ij}$). Similarly, the number of individuals working in each zone (W_j) can be estimated ($W_j = \sum_i T_{ij}$).

Isard (1960) provides a number of physical and social scientific justifications for the formulation in equation (1). Sen and Smith (1995) provide an exhaustive review. Flows between i and j are positively related to the "masses" of residences and workplaces and inversely related to the "impedance" (travel time) between i and j.

Estimates of the parameters yield a measure of the accessibility (A_i) of each residence zone to the workplaces which are distributed throughout the region (Isard, 1960, p. 510), i.e.,

$$A_i = \sum_j \hat{T}_{ij} / R_i^{\hat{\beta}} , \qquad (2)$$

where $\hat{T}$ is computed from the parameters of equation (1).

Suppose data are available on worktrip patterns of workers according to k education classes. A straightforward generalization of (1), expressed in logarithmic form, is

$$\log T_{ij} = \alpha' + \beta \log R_i + \sum_k \gamma_k \log W_j + \delta \log d_{ij} \qquad (3)$$

A comparison of (3) with (1) indicates the importance of the spatial disaggregation of workplaces by educational level. Analogously,

$$\log T_{ij} = \alpha' + \sum_k \beta_k \log R_i + \sum_k \gamma_k \log W_j + \delta \log d_{ij} \qquad (4)$$

A comparison of (4) with (3) indicates the importance of disaggregation of educational level by residence.

Finally, a completely disaggregated model can be compared,

$$\log T_{ijk} = \sum_k \alpha'_k + \sum_k \beta_k \log R_i + \sum_k \gamma_k \log W_j + \sum_k \delta_k \log d_{ij} \qquad (5)$$

More sophisticated measures of access recognize that the transport flows to each destination are count variables. The Poisson distribution is often a reasonable description for counts of events which occur randomly.

Assuming the count follows a Poisson distribution, the probability of obtaining a commuting flow T_{ij} is,

$$\text{pr}\,(T_{ij}) = e^{-\lambda_{ij}} \lambda_{ij}^{T_{ij}} / T_{ij}! \qquad (6)$$

where λ_{ij} is the Poisson parameter. Assuming further that,

$$\exp[\lambda_{ij}] = \alpha\, R_i^{\beta}\, W_i^{\gamma} / d_{ij}^{\delta} \ , \qquad (7)$$

yields an estimable form of the count model (since $E[T_{ij}] = \lambda_{ij}$). See Smith (1987) for a discussion. Estimates of the parameters similarly yield a measure of the accessibility of each residence zone to workplace in the region.

$$A_i = \sum_j \hat{\lambda}_{ij} / R_i^{\hat{\beta}} \ . \qquad (8)$$

As before, if worktrip patterns are available by educational level, this information can be incorporated into (7) in a manner analogous to (3), (4), and (5).

A more general model of the flow count between i and j relaxes the Poisson assumption that the mean and variance are identical. For example, following Greenwood and Yule, Hausman, Hall, and Griliches (1984, p. 922) assume that the parameter λ_{ij} follows a Gamma distribution $G(\omega_{ij})$ with parameters ω_{ij}. They show that, under these circumstances, the probability distribution of the count is negative binomial with parameters ω_{ij} and η,

$$\text{pr}\,(T_{ij}) = \frac{G(\omega_{ij} + T_{ij})}{G(\omega_{ij})\, G(T_{ij} + 1)} \left(\frac{\eta}{1+\eta} \right)^{\omega_{ij}} (1+\eta)^{-T_{ij}} \qquad (9)$$

Again, assuming that,

$$\exp\,[\omega_{ij}] = \alpha R_i^{\beta} W_j^{\gamma} / d_{ij}^{\delta} \quad , \tag{10}$$

yields an estimable form of the count model and the resulting accessibility index for each residence zone.

Again, the availability of worktrip patterns by educational level can be incorporated into (10) in a manner analogous to (3), (4), and (5).

The count models are clearly nested. If η is infinitely large, then equations (9) and (10) specialize to (7) and (8). If η is finite, then the mean and the variance of the count variables are not identical (as assumed by the Poisson representation).[1]

Data, Results, and Interpretation

The model is estimated using data on worktrips for the Stockholm metropolitan area for 1990. The data consist of commuting patterns by educational level among the 26 civil divisions in the metropolitan area. Also available is the average zone-to-zone commute time for the metropolitan area, by civil division. Since modal split is not treated explicitly, we have used commute time by car. Data are available separately for three educational levels corresponding to those with primary schooling, secondary schooling, and post graduates.

Figure 1 indicates the spatial pattern in worksites by educational level in the Stockholm metropolitan area. Figure 2 reports the pattern of residential locations by education level in the region. The patterns are decidedly non random, with the residences of the more highly educated workers concentrated in the northern part of the region.

Table 1 summarizes estimates of the parameters of the gravity model for these three educational groups. For each educational group, we present the parameters of the model based on the non-zero observations (out of 26 x 26 = 676 possible observations). The models are estimated by ordinary least squares. In addition to separate estimates by educational level, the table presents estimates of the model based upon worktrip distributions undifferentiated by educational level.

As the table indicates, each of the models explains a large fraction of worktrip behavior — ranging from 80 to 84 percent of the variance in log worktrips. Not surprisingly, the number of worktrips between jurisdictions varies positively with the number of available residences and workplaces. The number of worktrips is also highly sensitive to the commute time between origins and destinations. The coefficient on commuting time in minutes is large, negative, and highly significant. Importantly, the travel time coefficient declines with increases in educational level. An increased level of education is normally related to a higher income, and higher income to higher time values. Hence, it might be expected that the travel time coefficients

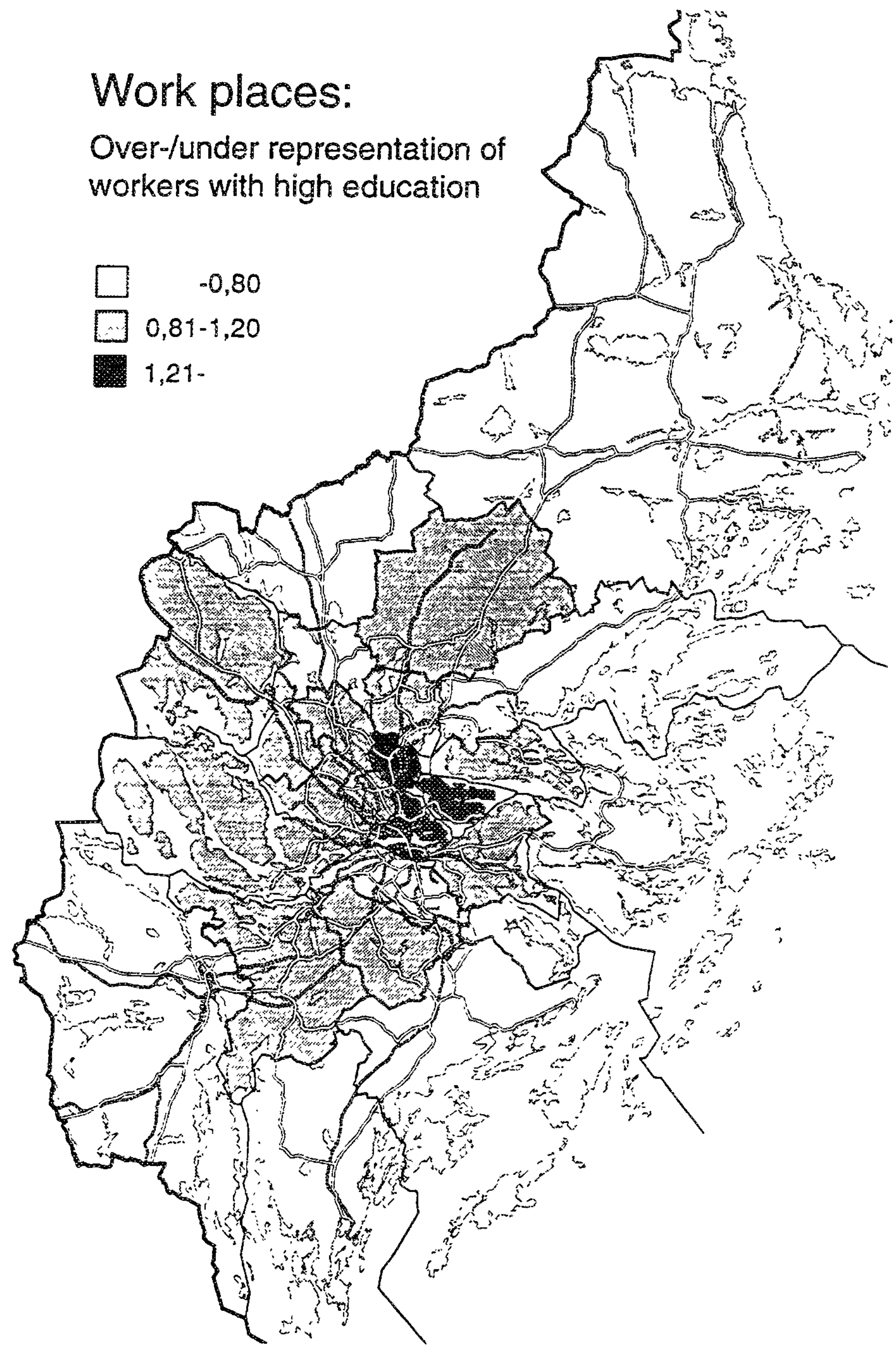
Work places:
Over-/under representation of workers with high education
-0,80
0,81-1,20
1,21-

Figure 1

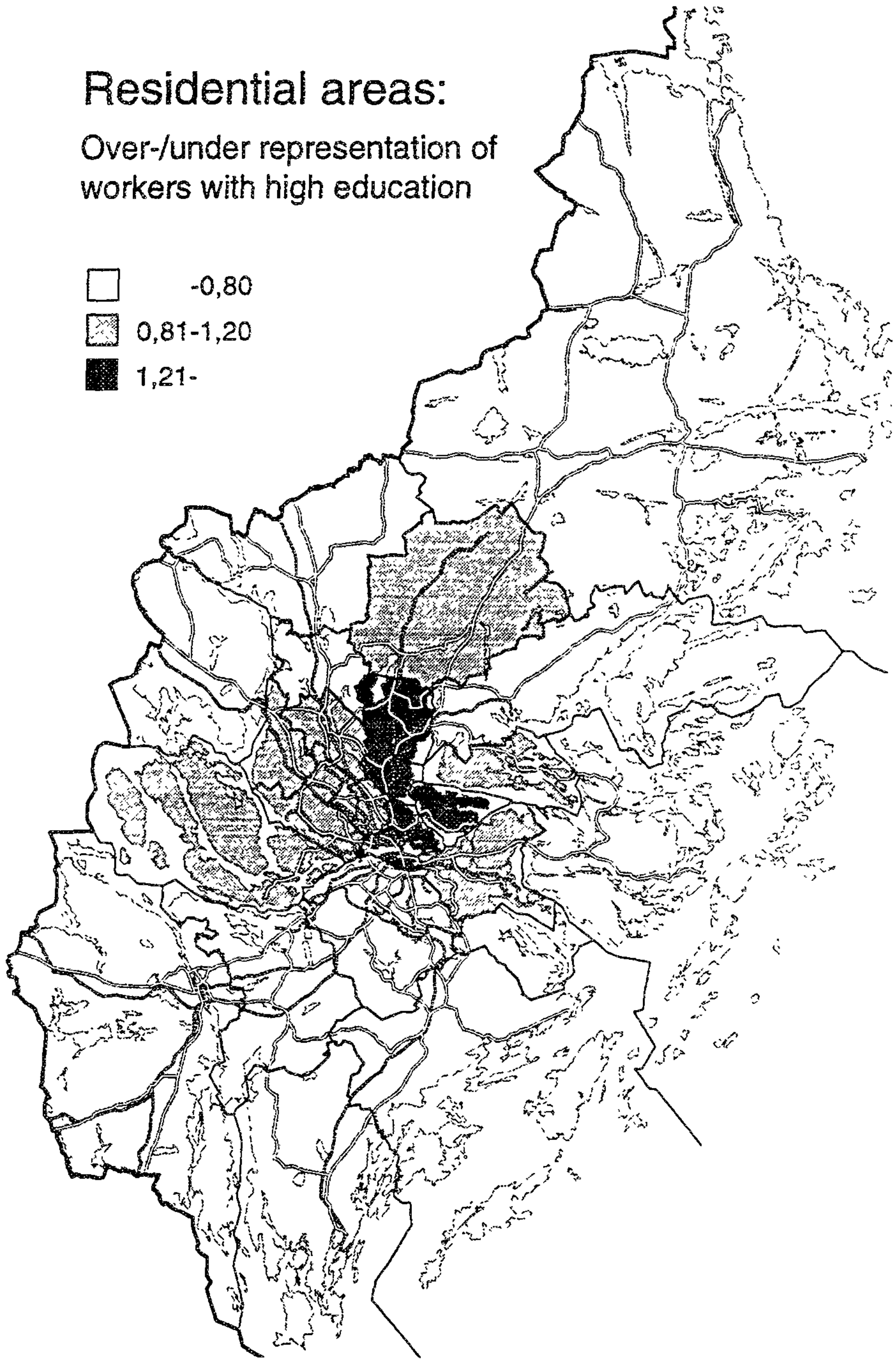
Residential areas:
Over-/under representation of workers with high education
-0,80
0,81-1,20
1,21-

Figure 2

Table 1. Parameters of Gravity Model Estimated Separately by Education Level (t-ratios in parentheses).

$$T_{ij} = \alpha R_i^{\beta} W_j^{\gamma} / d_{ij}^{\delta}$$

	Education Level			
	Low	Medium	High	Sum
α	-0.812 (1.34)	-0.053 (0.10)	0.500 (1.15)	-1.242 (2.22)
β	0.656 (13.12)	0.571 (13.63)	0.613 (17.92)	0.659 (15.63)
γ	1.117 (29.85)	1.058 (34.99)	0.938 (32.51)	1.129 (36.33)
δ	-2.844 (37.44)	-2.533 (36.10)	-2.378 (35.01)	-2.850 (43.53)
R^2	0.810	0.838	0.841	0.801
Observations	617	580	536	646

increase when the educational level increases. Our results indicate that this effect evidently is more than offset by the strong preference for space and different housing amenities among the best educated.

These general results are confirmed by the more rigorous results reported in Table 2 using the Poisson assumptions. The model coefficients are estimated by maximum likelihood using all 676 elements of the travel time matrix for each educational level. When the Poisson model is used to estimate access, the results are substantially more significant statistically. The t ratios of the coefficients increase by more than ten fold. Again, moreover, the coefficients vary significantly by educational level. The magnitudes of the coefficients are reasonably similar to those estimated by the gravity model. In particular, the effect of travel time in conditioning workplace choice and commute trip behavior declines as educational level increases.

These general results are confirmed by estimates of the negative binomial model. These estimates are not reported.[2]

In Table 3, the three matrices of worktrip behavior are combined in a single estimation. The table presents the coefficients of the gravity model based upon the combined sample of (626 x 3 = 2028) observations. The gravity model is estimated using ordinary least squares on the non-zero observations.

Six models are presented. Model I is identical in form to those presented in Table 1. It includes the number of workers residing in the origin zone, the number of jobs in the destination zone, and the travel time between zones. It is estimated on the 1733 non-zero observations.

Model II disaggregates the workers by origin zone into three educational levels.

Table 2. Parameters of Poisson Model Estimated Separately by Education Level (t-ratios in parentheses).

$$\text{pr}\,(T_{ij}) = e^{-\lambda_{ij}}\,\lambda_{ij}^{T_{ij}} \Big/ T_{ij}!\ , \quad \exp[\,\lambda_{ij}] = \alpha\, R_i^{\beta}\, W_j^{\gamma} \Big/ d_{ij}^{\delta}$$

	Education Level Low	Medium	High	Sum
α	1.270 (31.09)	0.861 (16.85)	0 568 (8.78)	0.723 (23.33)
β	0.571 (140.94)	0.567 (116.31)	0.626 (107.29)	0.553 (194.18)
γ	1.065 (354.93)	1.031 (300.60)	1.002 (229.78)	1.052 (519.87)
δ	-2.989 (425.48)	-2.637 (272.67)	-2.492 (179.72)	-2.844 (541.92)
χ^2	58047	25242	10363	89856
Observations	676	676	676	676

This disaggregation reveals significant differences by educational level. The disaggregation improves the explanatory power of the models by five percentage points.

Models III and IV present disaggregations by destination zone and distance, again revealing significant differences by educational level. The models explain roughly the same fraction of the variance in log worktrip behavior — about 83 percent.

Model V presents a disaggregation by the educational level of workers at origins as well as destinations. Model VI presents a complete disaggregation. Again the models reveal a systematic difference in the importance of travel time by educational level. There is a systematic decline in its influence as education level increases.

Table 4 presents a similar disaggregation using the more complex Poisson representation. Again, the significance levels of the parameters are much higher than for the gravity model. The results are much the same: The disaggregation by educational level at residence places and workplaces "matters" in a statistical sense in the prediction of commuting patterns and traffic flows. There is, moreover, a systematic decline in the importance of travel time in affecting behavior as levels of education increase.[3]

Figure 3 summarizes the partial effect of travel time on trip behavior as a function of educational level. The figure graphs the value of the access measure estimated from the Poisson model, $\hat{\lambda}_{ij}$, using model IV of Table 4. That is, holding the spatial distribution of supplies and demands for education constant for the three groups, it illustrates the decay in worktrip with distance.

Figure 4 indicates the cumulative frequency of worktrips by educational level implied by the same model. It indicates that there are substantial differences in

Table 3. Parameters of Gravity Model Estimated using Combined Samples of Commuting by Education Level. 1788 Observations (t-ratios in parentheses).

	I	II	III	IV	V	VI
α	3.802 (14.07)	0.290 (0.70)	0.336 (1.11)	-0.091 (0.30)	0.245 (0.82)	-0.794 (0.25)
β	0.327 (14.34)		0.590 (23.95)	0.615 (25.36)		
β_L		0.503 (22.56)			0.499 (15.42)	0.612 (16.95)
β_M		0.591 (24.41)			0.565 (17.94)	0.572 (16.74)
β_H		0.677 (25.23)			0 697 (22.48)	0.644 (19.89)
γ	0.864 (45.44)	1.034 (54.63)		1.038 (55.56)		
γ_L			0.936 (52.95)		1.034 (35.48)	1.092 (36.38)
γ_M			1.024 (53.14)		1.056 (39.04)	1.059 (37.85)
γ_H			1 109 (51.61)		1.008 (35.70)	0 958 (32.42)
δ	-2.712 (58.10)	-2.599 (61.60)	-2.610 (61.39)		-2.599 (61 58)	
δ_L				-2.780 (66.72)		-2.891 (46.81)
δ_M				-2.575 (60.78)		-2.531 (41.03)
δ_H				-2.404 (54.47)		-2.317 (35.86)
R^2	0.783	0.826	0.823	0.829	0.826	0.831

commuting behavior by education level — more highly educated workers are more likely to commute across community boundaries (as noted by the intercept) and are more likely to commute longer distances. For example, about 77 percent of workers of the lowest educational level are likely to commute twenty minutes or less, while only about 70 percent of workers of the highest educational level commute twenty minutes or less. At a half hour of commutation, the difference is about three percentage points in the cumulative distributions between the highly educated and the least educated population groups.

Table 4. Parameters of Poisson Model Estimated using Combined Samples of Commuting by Education Level. 2028 Observations (t-ratios in parentheses).

	I	II	III	IV	V	VI
α	2.131	1.181	1.178	1.051	1.177	1.002
	(80.70)	(42.19)	(42.04)	(37.09)	(42.02)	(35.08)
β	0.478		0.575	0.582		
	(182.23)		(209.25)	(211.72)		
β_L		0.549			0.559	0.591
		(204.44)			(184.13)	(171.43)
β_M		0.582			0.566	0.567
		(207.65)			(148.56)	(143.39)
β_H		0.632			0.628	0.600
		(212.91)			(137.68)	(129.03)
γ	1.012	1.043		1.043		
	(503.89)	(518.16)		(519.35)		
γ_L			1.015		1.030	1.070
			(506.44)		(378.88)	(361.16)
γ_M			1.049		1.058	1.029
			(511.95)		(336.26)	(303.06)
γ_H			1.096		1.047	0.997
			(507.04)		(263.90)	(230.00)
δ	-2.798	-2.818	-2.816		-2.817	
	(551.29)	(539.04)	(539.29)		(538.91)	
δ_L				-2.881		-2.969
				(542.29)		(443.43)
δ_M				-2.772		-2.652
				(520.99)		(307.76)
δ_H				-2.645		-2.552
				(486.59)		(226.51)
χ^2	106257	95345	95506	94039		93480

It should be emphasized that these comparisons assume that the spatial distribution of worksites and residences are the same for the three educational levels. In fact, these distributions are quite different; thus, the figures by themselves underestimate the importance of educational level on commuting.

The effects of variations in educational level upon commuting and trip-making behavior are quite substantial.

Conclusion

Each one of the three commuting models we have estimated shows that the sensitivity to commute time differs significantly between workers with different levels of education: the higher the education, the lower the influence of commute time.

In addition, the spatial distribution of worksites and residences differs among educational groups. In traditional models of access, it is implicitly assumed that all

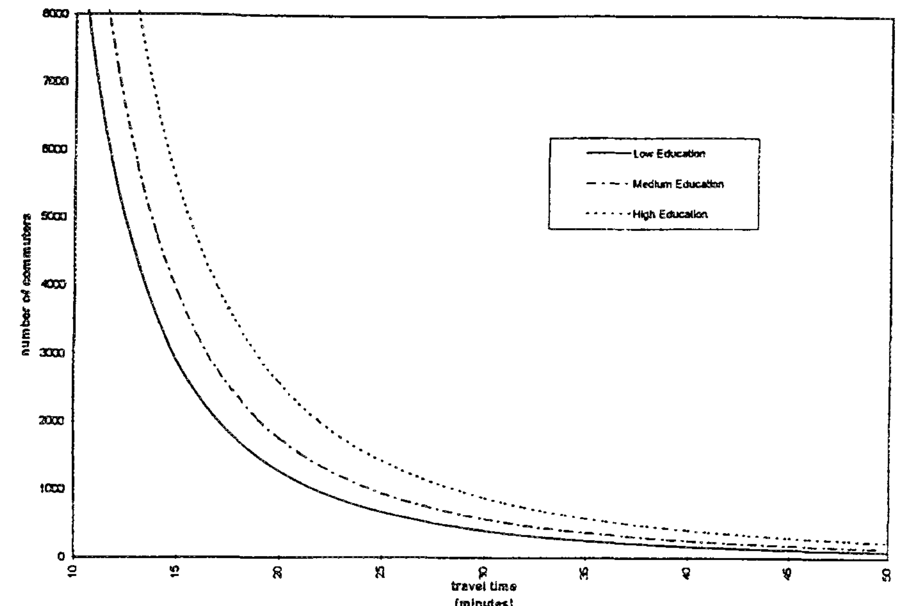

Figure 3.

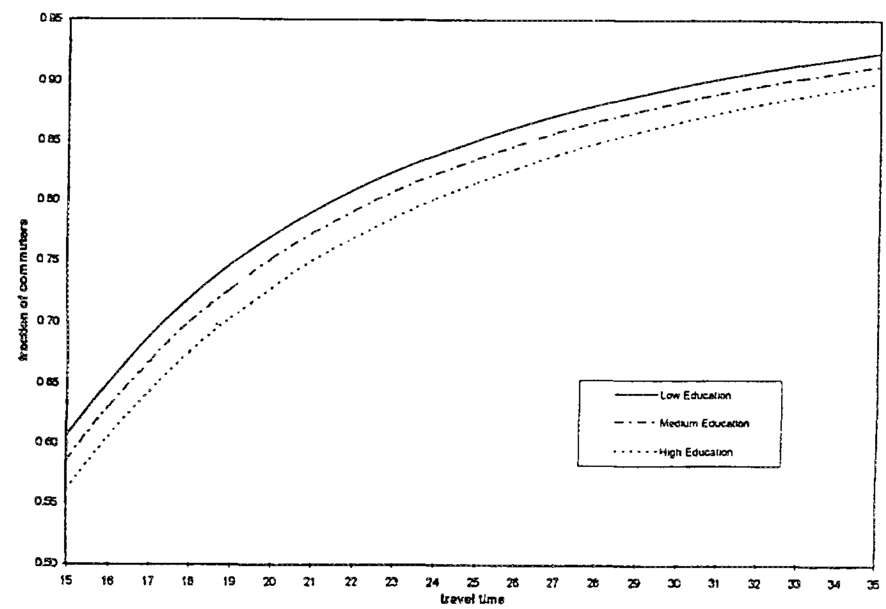

Figure 4.

workers are equally attracted to all kinds of jobs, and also that all workers have the same chance of getting any job. Our results indicate that it would be more fruitful to differentiate workers according to education in the analysis of traffic flows and employment potential.

Notes

1. It can be shown that the ratio of the variance to the mean is $[1+\eta]/\eta$.
2. These results are available from the authors on request.
3. Again, the results are similar when the parameters are estimated using the negative binomial model.

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