

**45th Conference of the European Regional Science Association
23-27 August Vrije Universiteit Amsterdam**

THE EFFECT OF INCOME ON COMMUTING TIME USING PANEL DATA

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ABSTRACT

Abstract: Urban economics theory predicts that households with higher incomes have different commuting time patterns than low income households. Empirical tests of this hypothesis are contaminated, due to reversed causation and lack of good control variables. In the current paper, we employ panel data to overcome these problems. To deal with reversed causation – that income, itself, is determined by commuting time as workers are willing to travel further for higher wages - we only select workers who did not change workplace location during the observation period. By using a fixed-effects model, the estimates are based only on differences in income and commuting over time for workers who remain in the same job, so that reverse causation is eliminated. In this case, changes in commuting time resulting from an income change come about either through a change in residence location or a change in travel mode. Our results show that the income elasticity of commuting time is positive but very small, 0.04.

Keywords: commuting, travel time, panel data, income elasticity

Acknowledgements: The BHPS data were made available through The Data Archive. Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

1. INTRODUCTION

Urban economics theories predict that individuals with higher incomes have different commuting time patterns than those with lower wages. However, there is a good deal of contention over the nature of this relationship. On the one hand, it is argued that high income earners will have shorter commuting times, because their time is more precious so that they wish to live closer to the job and pay for faster modes of travel. Because high income earners have a higher value of time, time spent commuting is very costly. Alternatively, it is argued that those with higher incomes will have longer commuting times, since higher incomes lead to a demand for better housing, more space and a higher quality of life which can more easily be obtained farther away from their workplaces. This is because rents and property prices tend to fall with distance from employment centers and suburban or rural areas generally have fewer social problems and less crime and provide a cleaner environment with more open space than central cities. A consequence of these conflicting influences is that according to urban economics theory the effect of income on commuting time is theoretically ambiguous.

Tests of the above hypothesis are not straightforward. One reason is that unobserved variables such as skills may affect commuting time and income, causing spurious correlation. Furthermore, labour economic theory argues that in a labour market characterised by incomplete information, commuting time has a positive effect on wage, because, given the residence location, jobs far away are more likely to be accepted if they offer higher wages (Manning, 2003). There is thus a simultaneity between the determination of the wage and of commuting time. Because of this, the wage variable is correlated with the disturbance in an model relating commuting time to the wage, so that the coefficient of wage cannot be estimated consistently by least squares regression. A common method of dealing with this problem is the use of an Instrumental Variable estimation procedure. The problem with this approach is finding suitable instruments for the wage variable. In this paper, we avoid the need for instruments by observing that commuting time may affect wages only when employees change job. Thus for individuals who remain in the same job, wages are not affected by commuting time, but are, in fact exogenous, so that the effect of income on commuting time can be estimated consistently by least squares regression. This model clearly cannot be estimated on the basis of cross-section data, in which differences in commuting time and wages between individuals result from their having different jobs and residential locations. Instead, we require observations of the commuting behaviour of individuals over

time (as well as information on their incomes and other relevant characteristics) and information on if and when they change employer. Such information is available in the British Household Panel Survey. In the current paper, we use these data to examine the effect of income on commuting time for workers who do not change employer over the observation period.

2. ECONOMIC MODEL

Suppose that w_{it} , c_{it} denote the income and commuting time for individual i in year t . We assume that commuting time can be represented by the following model:

$$\ln c_{it} = \alpha_i + \gamma \ln w_{it} + \beta x_{it} + u_{it} \quad (1)$$

where x represents observed control variables which influence commuting time and u_{it} is a random error. The effects of unobserved or omitted variables that are specific to the individual but are constant over time are represented by α_i . For example, these can have to do with the skills of the individual which cannot purely be measured by education and their tastes and preferences with respect to commuting. These effects can be fixed or random. If omitted individual-specific characteristics are correlated with the included explanatory variables, the estimated coefficients will be biased and inconsistent. The advantage of the fixed-effect model is that it prevents this type of specification error, so that (1) will produce consistent estimates. We can test for correlation between α and x and w using a Hausman test. If correlation is indicated, the fixed-effect specification is preferred to the random-effects specification.

In the fixed-effect case, since the individual-specific effect is assumed constant over time for each individual, it is perfectly correlated with measurable characteristics of the individual that do not change over time, for example, gender, race and perhaps educational level. These variables thus cannot be included in the model, and their effects on commuting cannot be estimated separately. Instead they are subsumed in the individual-specific intercept terms.

Consistent estimation of (1) also requires that w_{it} is exogenous to c_{it} and x . According to job search theory, this will not generally be the case, since the wage will depend positively on commuting. The motivation for this is that workers willing to travel longer distances have more job opportunities to choose from and thus are likely to obtain higher wages. *Changes in income*, however, will only depend on *changes in commuting distance* when an worker *changes employer* (Manning, 2003). When an individual *does not change job*, changes in commuting time can be explained by increasing (reducing) travel speed by switching to faster (slower) modes and moving residence closer to (further away from) the place of employment. By the inclusion of individual-specific fixed-effects in (1), only the variation in wages and commuting time (and the other included explanatory variables) for *each individual* is utilised in the estimation. For this reason, the fixed-effects estimator is also known as the within-estimator. Thus if (1) is estimated only for individuals who do not change job, the estimates will relate purely to *changes* in commuting time and income with a *given job*, so that reverse causation is eliminated, and β will provide an uncontaminated estimate of the effect of income on commuting time.

3. DATA

The British Household Panel Survey (BHPS) was established by the ESRC Research Centre on Micro-Social Change at the University of Essex in 1991. It provides a wealth of information for the study of social and economic change at the individual and household levels in Great Britain. Most relevant to this study are commuting time, income and information on when respondents change employer. In addition, there is a wide range of data on the individuals and households included in the survey: socio-economic and demographic characteristics, residential location, etc.

The BHPS was designed to be representative of all households in Great Britain in the year of its inception, 1991. It is, thus, a stratified sample rather than a random sample. So far, 13 years or “waves” of data have been released encompassing the years 1991 to 2003. The initial sample contained over 5000 households and it has not been refreshed over the years, but particular effort has been made to avoid attrition. Because of this, the attrition rate in the BHPS is lower than in most panel surveys. In the year 2001, 59% of the households initially interviewed in 1991 still remained in the survey, and 52% of the original households gave full

interviews in each of the 11 years. Despite the comparatively low attrition rate, the sample has become less-representative of the British population over time.

Data from 11 years of the BHPS are used in this study (1991 to 2001). The analysis of travel to work is based on the individual, and only on those individuals who travel to work. There are 5,439 individuals in the 1991 sample and in 2001 there are 4,942 individuals. These are not necessarily the same individuals, since some leave our sample as they retire or become unemployed and some enter the sample as when they begin or return to work. All of these individuals are members of the households originally interviewed in 1991.

The mean one-way travel time for all commuters in 2001 was in minutes 23 minutes. The mean by income quartile in 2001 is shown in Table 1. Mean travel time clearly increases with income, from 18 minutes for those with the lowest incomes to 33 minutes for the highest earners. No conclusion can be drawn about the direction of causation from these numbers, since the relationship between commuting time and income reflects both the impact of longer travel distances on income and the influence of increasing income on commuting time.

4. EMPIRICAL RESULTS

The model in (1) was estimated for the individuals in the BHPS who travel to work and do not change employer during the period in which they participate in the survey. This provides a sample of 38511 observations of 9357 individuals. Each individual is observed for an average of 4 years, and slightly over 10% for all 11 years.

The dependent variable in the model is the log of one-way door-to-door commuting time in minutes. The independent variables are the log of real income (in year 2000 £) and dummy variables denoting whether the individual is single (as opposed to married or co-habiting), whether any other members of the household are also employed and whether there are children in the household.

The econometric results are shown in Table 2. The first column reports the estimates of the Fixed-Effects model in equation (1). The Hausman test at the bottom of the column strongly indicates the existence of correlation of the omitted individual effects with the included independent variables, so that their omission would lead to biased estimates. Our choice of

the fixed-effects model is thus confirmed statistically. In addition, the F-test strongly rejects the equality of the intercept coefficients (fixed-effects). The adjusted R^2 value shows that the model explains the data reasonably well, and the estimated autocorrelation indicates that serial correlation is not a problem. The coefficient of the income variable is very highly significant, and the other variables are significant at the 5% level or 10% level.

Since both commuting time and income are in log form, the income elasticity of commuting time is given by the coefficient of the income variable. The estimated elasticity of 0.04, is small, but positive, suggesting that an increase in income, with a given job, increases commuting time. The effect, however, is only marginal. A 10% increase in income, for example, results in an increase in commuting time by 0.4%. With a travel time of 20 minutes, a 100% increase in income would be required to increase travel time by 1 minute. Since the individual does not change job, this increase in travel time must be the result of moving further away from the place of employment.

The coefficients of the other explanatory variables yield some interesting results. The negative coefficient of “Single” indicates that when an individual ceases living with a partner, their commuting time declines, presumably as he/she moves closer to their job. Alternatively, marriage or cohabitation leads to an increase in commuting time, presumably as there is a tendency to move farther from the job of at least one of the individuals. If other household members become employed, commuting time for the original worker increases marginally, perhaps because of a move closer to the workplace of the other individual or the sharing of the household car for commuting. Finally, when the individual has a child, commuting time decreases. This suggests that the individual moves closer to the workplace or travels by a faster mode to be able to spend more time with the child.

Estimates for number of other models are also shown in the table. The second column assumes that the individual-specific effects are random (but constant over time). This model was rejected by the Hausman test, and we see the estimated parameters differ somewhat from the fixed-effects model. Most obvious is the increase in the income effect, which is nearly twice that of the previous model. This is to be expected because the random-effect estimator uses differences between individuals as well as differences over time for the same individual, so that the estimate of the income parameter includes the reverse causation of commuting

distance on income. The effect of income on commuting time can thus not be distinguished from these estimates.

The fourth column shows the result if the fixed-effect model which includes time along with the other explanatory variables. The coefficient of time is positive and highly significant suggesting that commuting time increases over time as the result of some factor not included in the model which is the same for all individuals. An example could be congestion, although it is unlikely that this should affect all individuals to the same degree. Alternatively it could be capturing the fact that individuals are becoming older, and more likely to move further away from their workplaces. However, we would expect this effect to decline after a certain age. Otherwise, the estimated parameters are very similar to the original fixed-effects model. The decline in the income elasticity could be explained by the tendency of income to increase as the individual ages. The final column shows the same model with the variances corrected for heteroscedasticity using White's method. The significance of the estimated coefficients is only slightly affected, indicating that heteroscedasticity is not a problem.

5. CONCLUSIONS

The objective of this paper was to determine the effect of income on commuting time. Using a fixed-effects model and panel data observations of individuals who remain in the same job over the observation period, reverse causation is eliminated. In this case, changes in commuting time resulting from an income change come about either through a change in residence location or a change in travel mode. Our results show that income has a positive, but small effect on commuting time in the UK, with an income elasticity on the order of 0.03 to 0.04. These results suggest that the conflicting influences of increasing income on commuting time - the positive impact of the demand for higher quality housing and the negative impact of an increasing value of time demand - more-or-less cancel out. Further empirical work, however, is needed to confirm this result.

References

Manning, A. (2003), The real thin theory: monopsony in modern labour markets, *Labour Economics*, 10, p.105-131

Table 1 Commuting time, one-way, in minutes by income quintile, 2001, BHPS

Income Quintile	1	2	3	4	5
Commuting time	18	19	23	26	33

Table 2 Regression results: dependent variable log of commuting time, t-values in parenthesis under the estimated coefficients

Variable	Fixed Effects	Random Effects	Fixed Effects	Fixed Effects Heteroscedasticity corrected errors
Ln Real Income	0.04 (8.40)	0.07 (18.84)	0.03 (6.89)	0.03 (5.65)
Single	-0.03 (2.49)	-0.02 (2.14)	-0.03 (2.50)	-0.03 (2.38)
Others employed in HH	0.01 (1.54)	0.01 (1.20)	0.02 (1.89)	0.02 (1.88)
Children in HH	-0.04 (2.43)	-0.05 (6.12)	-0.03 (3.07)	-0.03 (2.92)
Time			0.01 (7.50)	0.01 (7.39)
Adjusted R ²	0.682		0.683	0.683
Estimated autocorrelation	0.045		0.044	0.044
F-test (versus $\alpha_i = \alpha$ for all i)	9.21		9.31	9.31
degrees of freedom	9382,29124		9382,29123	9382,29123
Hausman Test	171.0		201.7	86.2
degrees of freedom	4		5	5

* coefficients in **bold** significant at the 5% level, in **bold italics** at the 10% level