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## Advanced telematics for travel decisions: a quantitative analysis of the Stopwatch project in Southampton

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**Abstract.** The effect of telematics technology on public transport use is analyzed on the basis of a theoretical model. Two possible mechanisms (reduction of uncertainty and a better choice of bus options, based on a general cost-minimization assumption) that may stimulate bus use are distinguished. The model is empirically tested by using microdata from the Southampton Stopwatch telematics project, which were collected both before and after the introduction of this telematics information service. The estimation of the model leads to interesting findings in explaining (anticipated) increases in bus use, for both the before and the after survey. It is shown that uncertainty reduction is the more important effect of the new system. Differences in the before and after data are found concerning the increase in bus use, but the explanatory model proves consistent over the two samples.

### 1 Introduction

In recent years several telematics technologies have been developed to offer better information to travellers, so that the utility rise for potential users will encourage them to choose public transport more frequently.<sup>(1)</sup> In public transport this information concentrates on departure times, improving the accuracy of the travellers' estimates of these times. The lack of certainty about departure times of public transport is considered to be one of the major obstacles in the way of an increased use of public transport.

The aim in the present paper is to provide a solid economic analysis of the question of how provision of information on arrival (or departure) times of public transport (with particular emphasis on buses) impacts on the use of the mode. We assume that two potential mechanisms are at work here. The first is that the reduction in the uncertainty about how long travellers have to wait at the bus stop allows them to make better use of this waiting time. The second mechanism is that travellers can make a better choice among the services available to them (assuming that multiple services satisfy their demand), which by definition decreases their overall expected trip costs. Notice that the first mechanism also reduces overall expected trip cost by the potential substitution of waiting (a cost factor) by an alternative activity (by definition a preferable activity). Clearly, because both of the effects of information provision lead to a decrease in expected overall cost, the impact on bus use can only be nonnegative. The analysis is complemented by an empirical test on survey data of individual trip-making behaviour of travellers.

The paper is organized as follows. Section 2 is devoted to the economic foundation and analysis of the above-mentioned mechanisms. In section 3 we describe a recent

<sup>(1)</sup> It should be noted that telematics applications have been applied in many directions for solving general transportation problems (congestion, environmental damage, etc). Two main applications in this field are route guidance, to optimize road usage (Emmerink et al, 1995; Mahmassani and Jayakrishnan, 1991) and telecommuting (Mokhtarian and Salomon, 1994; Soekkha et al, 1990). A broad overview of methodologies and applications in telematics research can be found in Nijkamp et al (1996).



telematics project in Southampton, in which some of these issues play an important role. Next, in section 4 we present our statistical investigations. The paper concludes with some strategic observations on the importance of telematics systems in public transport.

## 2 Analyzing the effect of information provision

### 2.1 The basic model

Suppose a traveller  $T$  wants to make a trip for which two alternative modes are available, namely bus and car. Assume that  $T$  is a cost minimizer and let  $C_a$  be the cost of using the car and that this cost consists only of a fixed amount  $F_a$ , and let  $C_b$  be the cost of using the bus.

The costs of using the bus are assumed to consist of three parts: a fixed cost  $F_b$ , the cost of waiting itself, and a cost associated with the uncertainty involved in waiting. Isolating waiting from the general costs, which include in-vehicle time, is justified by the notion that people value waiting time two or three times higher than in-vehicle time (Mohring et al, 1987). The inclusion of waiting-time cost is based on an opportunity-cost approach. The cost due to uncertainty as explained above is in essence also a measure of opportunity cost. This may seem to be a sort of double counting but it is not. Uncertainty factually prohibits an alternative activity during waiting. It seems reasonable to assume that  $U(\text{no waiting}) > U(\text{alternative activity during waiting}) > U(\text{just waiting})$ , with  $U(\cdot)$  any utility function. The cost of waiting reflects the difference between  $U(\text{just waiting})$  and  $U(\text{no waiting})$ , and the cost of the uncertainty relates to the possibility of recapturing some of this disutility by doing something else. Therefore both the waiting time and the uncertainty are involved as cost terms.

Hence the cost of taking the bus for a given trip can be formulated as

$$C_b = F_b + \alpha W + \beta \sigma^2, \quad (1)$$

where waiting time,  $W$ , is multiplied by a factor,  $\alpha$  ( $\alpha \geq 0$ ), which is a measure of the time value, and the variance of the waiting time,  $\sigma^2$ , is a cost measure of the uncertainty, weighted by a factor  $\beta$  ( $\beta \geq 0$ ). Traveller  $T$  will compare these costs with  $F_a$  which is the generalized cost of the alternative.

### 2.2 The effect of uncertainty reduction

In this subsection we concentrate on uncertainty reduction, neglecting the waiting time  $W$  by assuming  $\alpha = 0$ . As  $T$  is a cost minimizer, for some given trip he or she will choose the bus if

$$F_b + \beta \sigma^2 < F_a,$$

or

$$F_a - F_b > \beta \sigma^2. \quad (2)$$

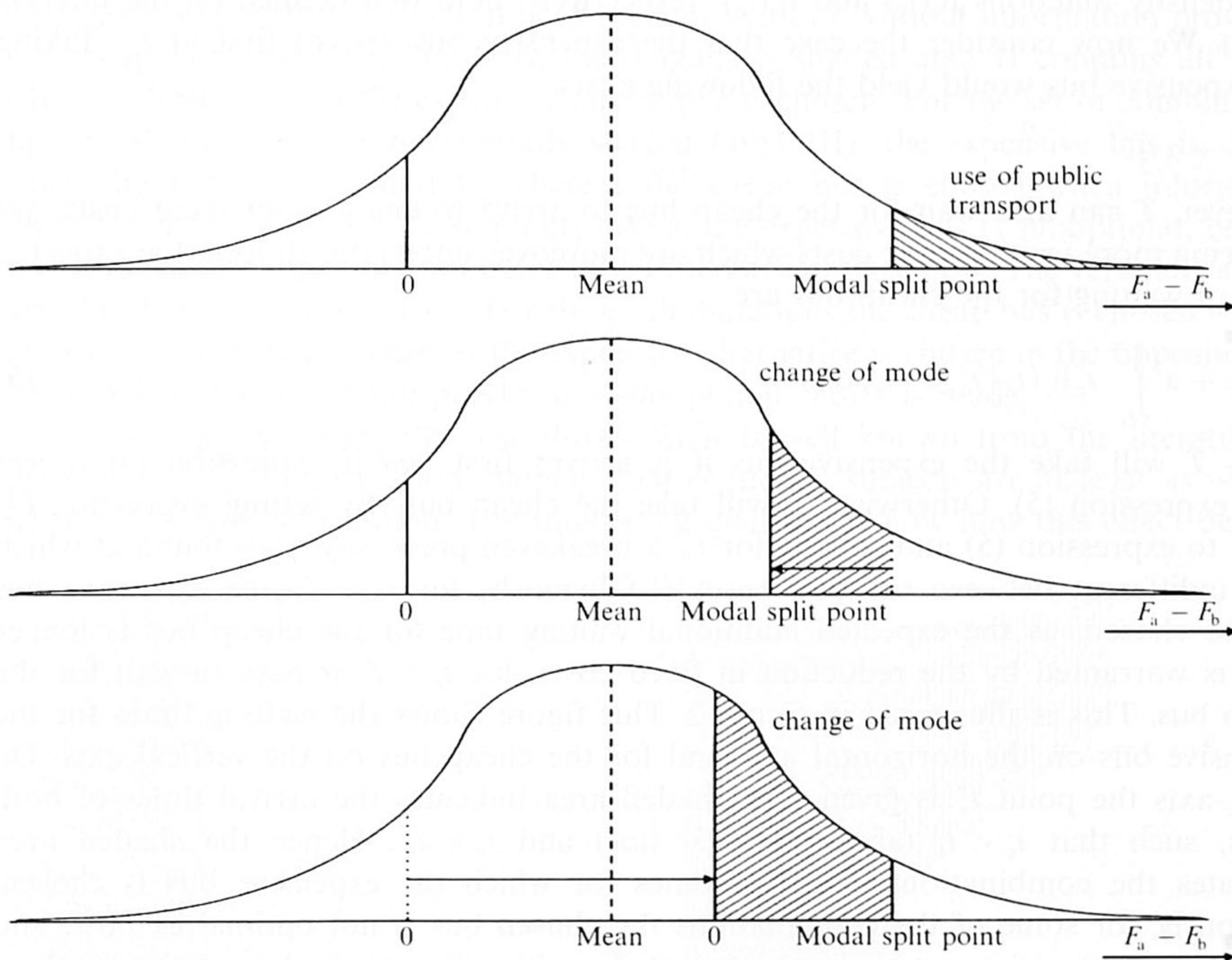
We now assume that  $T$  considers a large number of trips during a given time period and that the term  $F_a - F_b$  involved in all these trips follows some probability distribution. Suppose, for example, that this distribution is normal with mean  $m$ ,  $m > 0$ , see figure 1(a). Referring to condition (2),  $T$  will choose the bus for all cases where the difference in fixed cost is greater than  $\beta \sigma^2$ ; the point at which the difference in fixed cost equals  $\beta \sigma^2$  will be called the modal-split point (ms point).

The effect of reducing the uncertainty is a shift of the ms point to the left [see figure 1(b)]. The share of trips for which a change of mode occurs is given by the shaded area. Consequently, the impact of a fixed reduction in uncertainty is dependent on



three factors: first, the magnitude of the reduction in uncertainty,  $\sigma^2$ ; second, the magnitude of the parameter  $\beta$ —these two factors together determine the size of the shift of the ms point along the  $x$ -axis; and third the location (and shape) of the distribution function.

The notion that the effect also depends on an unknown distribution function is quite important. It shows that the largest effect of providing better information is not necessarily to be expected to occur with those travellers who do not often travel by bus. Ad hoc reasoning would make this seem plausible as less frequent bus travellers have a large potential for using the bus. The model shows, however, that the potential increase in bus use is not only determined by the share of trips, left of the ms point, but is also restricted to be on the right of the  $y$ -axis, because uncertainty cannot become negative [see figure 1(c)]. Notice by the way, that this type of reasoning holds for any cost factor, which does not allow an interpretation as a benefit when it becomes negative.



**Figure 1.** (a) The modal split with uncertainty; (b) change in modal split caused by uncertainty reduction; (c) influence of location of distribution.

**2.3 The effect of improved optimality in type choice**

The second effect of information provision is the improvement in choosing among various types of public transport. In particular, assume that the traveller has two possibilities at the bus stop and that he or she receives information about the arrival times of both buses. Our goal is to analyze how the improved optimality of the choice between these types affects the attractiveness of the mode in general. Concentrating on the variable  $W$  we simplify model (1) by assuming  $\beta = 0$ .

Suppose  $T$  can choose between two alternative types when taking a bus, a cheap and an expensive one. The cost functions for the buses are now given by

$$C_i = F_i + \alpha W_i, \quad i = e, c, \tag{3}$$



where  $W_i$  represents the waiting time for bus  $i$ , and  $e$  and  $c$  index the expensive and cheap bus, respectively.  $T$  chooses the bus if the minimum over  $i$  of the expectation of equation (3) is less than  $C_a$ . We will show that information about arrival times has a nonnegative effect on equation (3), and hence increases the probability of  $T$  taking the bus.

Suppose that  $T$  is at the bus stop, and is optimizing his or her (type of) bus-choice problem. Let  $t_c$  and  $t_e$  be the waiting times for the cheap and expensive bus, respectively. Clearly  $T$  will choose the cheap bus if  $t_c < t_e$  (that is, the cheap bus arrives first) because then both cost elements (fixed cost and waiting time) are smaller for this alternative. Moreover, in certain cases  $T$  may choose the cheap bus even if the expensive one arrives first, and hence an extra waiting-time cost is incurred. This will happen when the expected remaining waiting time for the cheap bus is sufficiently small that the extra cost of taking the expensive bus outweighs the cost of a longer waiting time.

To proceed, suppose that the waiting times for both bus types are random variables with density functions  $h_c(t_c)$  and  $h_e(t_e)$ , respectively, both well defined on the interval  $[0, \infty)$ . We now consider the case that the expensive bus arrives first at  $t_e$ . Taking the expensive bus would yield the following costs:

$$F_e + \alpha t_e. \quad (4)$$

However,  $T$  can also wait for the cheap bus to arrive to enjoy lower fixed costs, yet incurring more waiting-time costs which are moreover uncertain. Indeed, the expected costs of waiting for the cheap bus are

$$F_c + \alpha \int_{t_e}^{\infty} t_c h_c(t_c | t_e > t_e) dt_c. \quad (5)$$

Thus,  $T$  will take the expensive bus if it arrives first *and* if expression (4) is less than expression (5). Otherwise,  $T$  will take the cheap bus. By setting expression (4) equal to expression (5) and solving for  $t_e$ , a breakeven point, say  $t_e^*$ , is found at which  $T$  is indifferent between the two buses.<sup>(2)</sup> Obviously, for  $t_e < t_e^*$ , the expensive bus will be chosen, as the expected additional waiting time for the cheap bus is longer than is warranted by the reduction in fixed costs; for  $t_e > t_e^*$  it pays to wait for the cheap bus. This is illustrated in figure 2. This figure shows the waiting times for the expensive bus on the horizontal axis and for the cheap bus on the vertical axis. On the  $t_e$ -axis the point  $t_e^*$  is given. The shaded area indicates the arrival times of both buses, such that  $t_e < t_c$  (above the 45° line) and  $t_e < t_e^*$ . Hence the shaded area indicates the combination of arrival times for which the expensive bus is chosen. Obviously, for some of the combinations the chosen bus is not optimal ex post, and information provision can help to prevent  $T$  making the wrong bus choice in these cases. This is now analyzed below.

Suppose that the expensive bus arrives first at  $t_e$ , and that  $T$  gets information about the (expected) arrival time of the cheap bus. Hence  $T$  will now compare expression (4) with a new expression for the expected cost of taking the cheap bus:

$$F_c + \alpha t_c. \quad (6)$$

<sup>(2)</sup> We assume that a unique  $t_e^*$  exists. It is not obvious what the conditions for this uniqueness are. In any case it can easily be shown that when the distribution is normal, this uniqueness is guaranteed (see the appendix) while assuming an exponential distribution gives either infinitely many or no solutions, depending on whether or not  $(F_e - F_c)/\alpha = 1/d$ , with  $d$  the expectation of the exponential distribution. We conjecture that unimodularity and continuity is a sufficient condition for uniqueness, when this mode is in the range on which the distribution is defined (not on the endpoints, as is the case for an exponential distribution). An anonymous referee is acknowledged for making some helpful comments on this point.



In this case  $t_c$  is no longer a random variable, but is the arrival time revealed by the information.<sup>(3)</sup> Comparing expression (4) with expression (6) gives a condition for the arrival times, so that the expensive bus is chosen. This condition reads as

$$\alpha t_e + F_e < \alpha t_c + F_c,$$

or

$$t_c > t_e + \frac{F_e - F_c}{\alpha}. \tag{7}$$

Notice that this latter condition implies  $t_c > t_e$ . The combination of arrival times for which condition (7) holds can be drawn in a way similar to that in figure 2. Figure 3 has been drawn to compare the situations with and without information. This figure can be used to demonstrate that information has the unequivocal effect of decreasing the expected cost of using the bus.

In figure 3 the  $(t_e, t_c)$  space is divided into four areas. The unshaded area I represents all points for which in both regimes (with or without information provision) the cheap bus is chosen. Similarly, the diagonally shaded area II contains all points where in both regimes the expensive alternative is chosen. For the set of combinations of arrival times that is horizontally shaded (area III), the expensive bus is chosen when there is no information, whereas the cheap bus is chosen when information provision is in effect. For these points taking the expensive bus is suboptimal, because the extra waiting time does not exceed the difference in fixed cost. The vertically shaded area IV shows the reverse case. For these combinations the cheap bus is chosen without information provision, whereas the expensive alternative is chosen in the opposite case. Again without information provision a suboptimal choice is made.

So far we have basically just shown what is well known from the literature on the economics of information, namely, that economic subjects are at least as well off when using free information. The interesting question is now how this effect depends

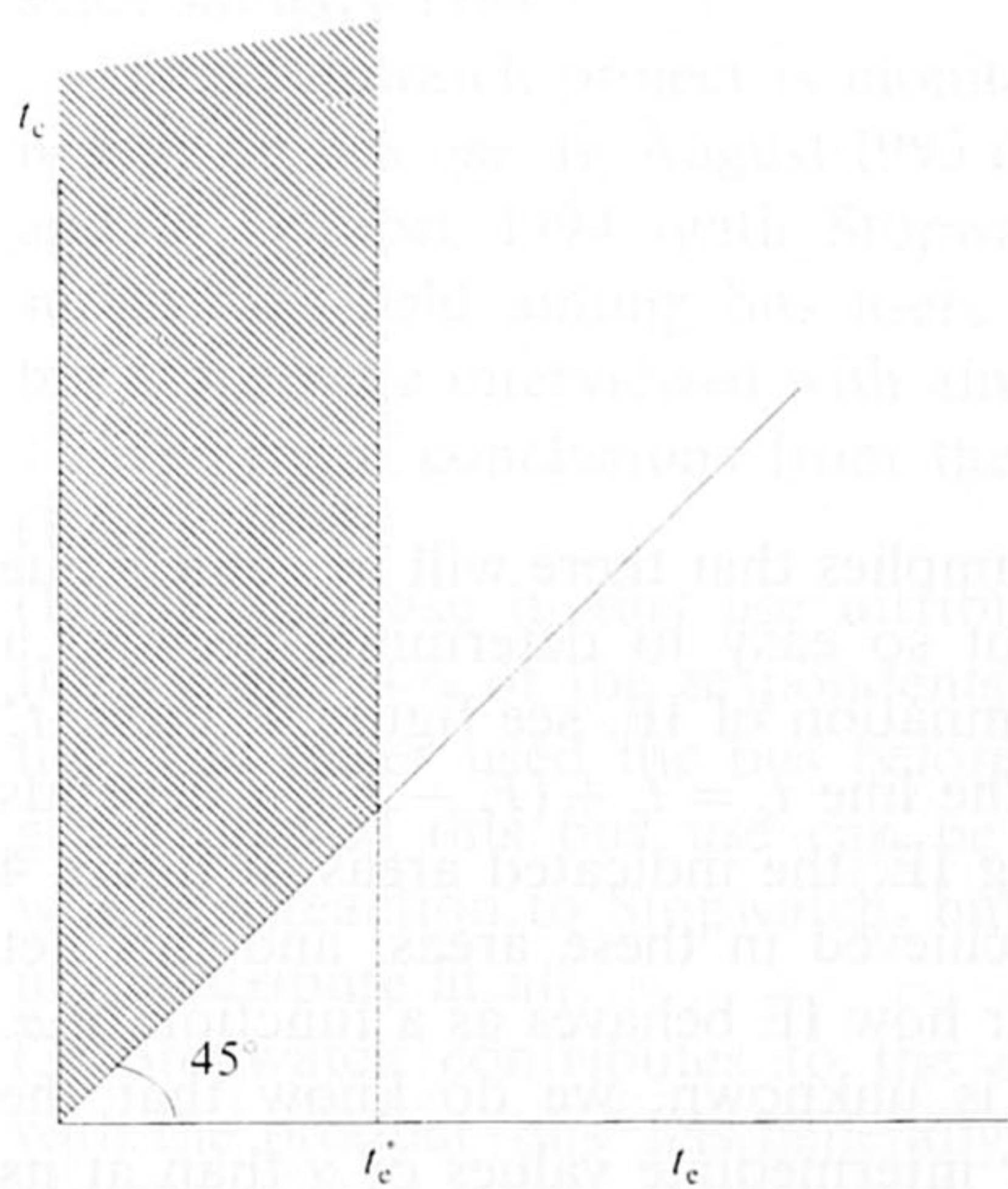


Figure 2. Bus choice without information.

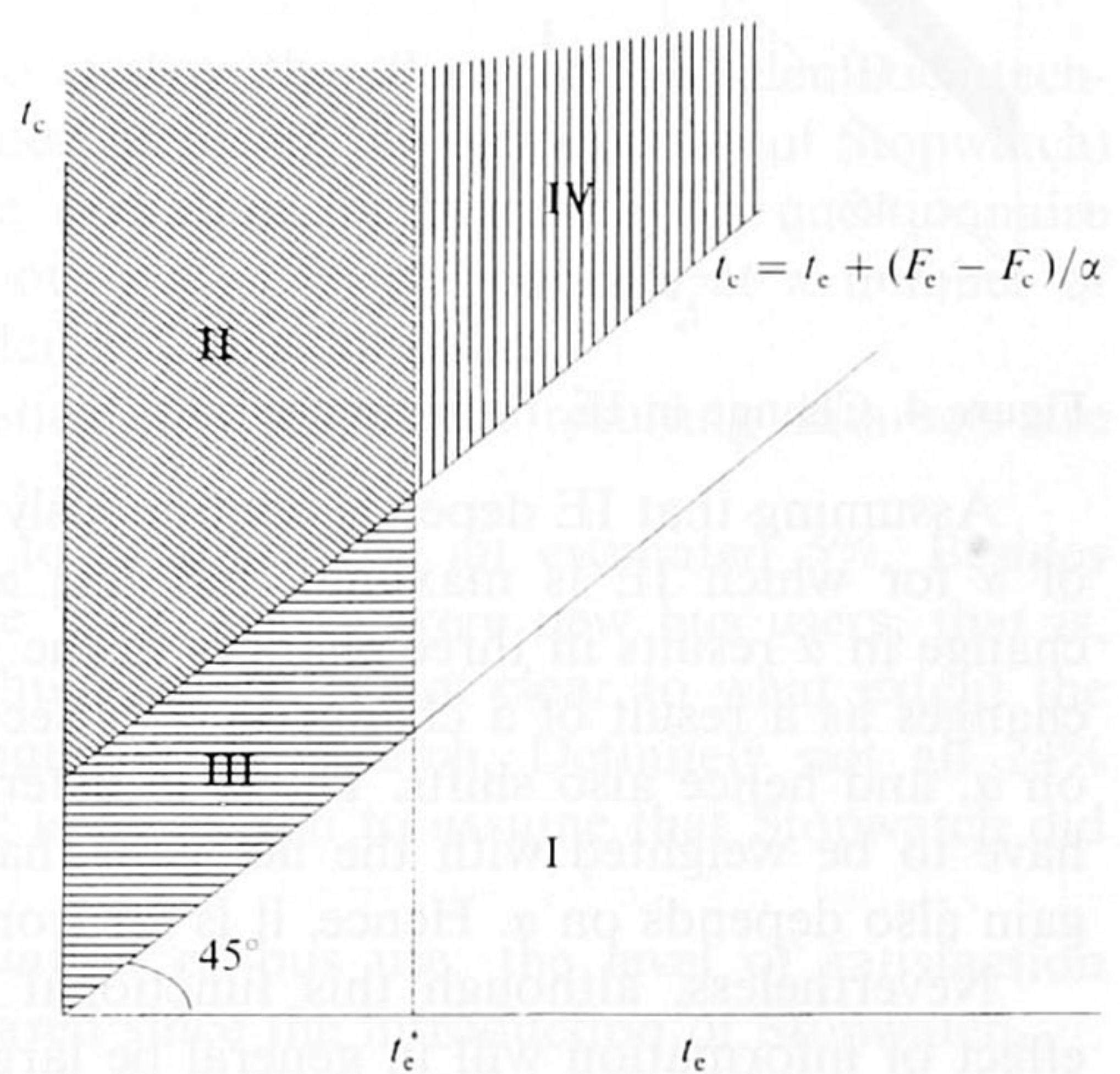


Figure 3. The information effect.

<sup>(3)</sup> Even if  $T$  considers the arrival time  $t_c$  as a random variable, it is reasonable to assume that the expectation of this variable is again the one indicated, so that expression (6) still holds. A further complication may be introduced, however, by assuming that  $T$  does not adopt the indicated arrival time as the new expected arrival time, but rather adjusts a prior expected time with the information from the display. This would not affect the following demonstration substantially, however.



on other parameters of the problem, and in particular on the  $\alpha$  coefficient representing the value of time. It seems intuitively plausible that travellers with high values for  $\alpha$ , that is, those with a high time preference, will profit most from information provision, as the information typically has an effect on waiting times. Analyzing the above model reveals, however, that this is not unequivocally so. This follows directly by observing the effect at three distinct values for  $\alpha$ , namely when  $\alpha = 0$ , the value for  $\alpha$  which gives  $t_c^*$  as indicated in figure 3, and a very large value of  $\alpha$ , approaching infinity.

When  $\alpha = 0$ ,  $T$  attaches no cost at all to waiting. From expression (4), it follows immediately that the cheaper bus will be taken, no matter how long  $T$  has to wait for this bus, and this result is independent of the presence of any additional information. From figure 3 we can see that as  $\alpha$  tends to zero the  $t_c^*$  line shifts towards the  $y$ -axis and for some value of  $\alpha$  (not necessarily zero) eventually coincides with it. At the same time the line given by  $t_c = t_e + (F_e - F_c)/\alpha$  shifts upwards. The result is that both the areas III and IV vanish. Hence the effect of information is zero when  $\alpha$  is zero. Similarly, when  $\alpha$  tends to infinity, the value of time is so high that  $T$  will always take the first bus to arrive, again independent of the additional information. In terms of figure 3, the line given by  $t_c = t_e + (F_e - F_c)/\alpha$  now shifts downwards and ultimately coincides with the  $t_c = t_e$  line. Also  $t_c^*$  shifts to the right and the effect again is that areas III and IV vanish. Thus, the effect of information provision is zero. In between these extreme values, however, there will be— clearly illustrated in figure 3— values of  $\alpha$  for which the information effect (IE) is strictly positive.

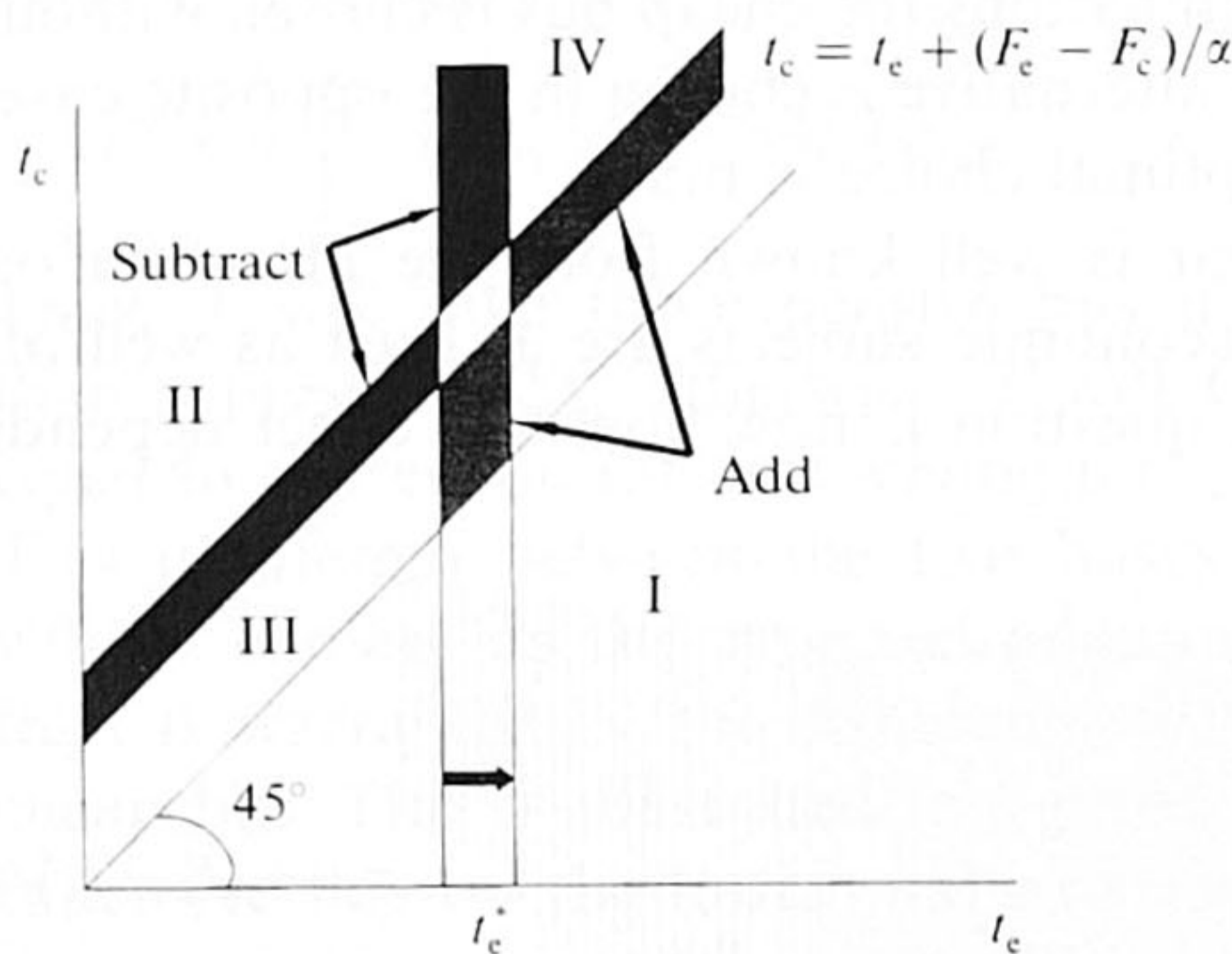


Figure 4. Change in IE, from change in  $\alpha$ .

Assuming that IE depends continuously on  $\alpha$  implies that there will be some value of  $\alpha$  for which IE is maximal, but this  $\alpha$  is not so easy to determine, because a change in  $\alpha$  results in three changes in the determination of IE, see figure 4. First,  $t_c^*$  changes as a result of a change in  $\alpha$ .<sup>(4)</sup> Second, the line  $t_c = t_e + (F_e - F_c)/\alpha$  depends on  $\alpha$ , and hence also shifts. Third, in determining IE, the indicated areas in figure 4 have to be weighted with the net gain that is achieved in these areas, and this net gain also depends on  $\alpha$ . Hence, it is far from clear how IE behaves as a function of  $\alpha$ .

Nevertheless, although this functional form is unknown, we do know that the effect of information will in general be larger for intermediate values of  $\alpha$  than at its limits. For practical purposes we may assume a unimodal functional form.

### 3 The Stopwatch project in Southampton

Our case study concerns the application of a real-time passenger-information system, called Stopwatch, in the urban area of the city of Southampton (United Kingdom).

<sup>(4)</sup> A positive relation between  $\alpha$  and  $t_c^*$  is conjectured. This is further investigated in the appendix.



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Stopwatch is part of the SCOPE field trial project.<sup>(5)</sup> SCOPE stands for Advanced Transport Telematics (ATT) applications in Southampton, Cologne, and Piraeus. The emphasis of this project was on improving information infrastructure by providing accurate and timely traffic information. The overall objective was to increase the efficiency of the network by increasing the share of public transport in the modal split, which would be accompanied by a reduction in automobile traffic congestion.

Within SCOPE and ROMANSE (Road Management System for Europe), for Southampton, a computer model and control system were created for integrated urban transport management. The particular ATT systems developed and tested on this site are the provision of multimodal schedule information, technologies for the location and identification of public transport vehicles, and the integration of schedules with real-time information.

The real-time information system Stopwatch for bus users involves the equipping of bus stops with electronic signs which can give minute-by-minute information about approaching vehicles as well as about delays and disruptions to services. The information provided to passengers covers the next five approaching buses, their destinations, and an accurate estimate of when they will actually arrive at the stop. These 'intelligent' bus stops are fed continuously with data from the Automatic Vehicle Location (AVL) system, which incorporates equipment on buses and along the bus routes (beacons). By means of dead reckoning an estimation of the position of the respective buses is made, and passed on to a Traffic and Travel Information Centre (TTIC), which forwards the information to the bus stops. The specific aim of Stopwatch was to improve the overall quality of bus services which might in turn increase patronage.

The Stopwatch system operates in a deregulated environment and provides information on a trial corridor for eleven services operated by two different bus operators serving Southampton, Southampton City Bus (nine services) and Solent Blue Line (two services). In total 44 bus stops have been equipped with displays, receiving data from 144 vehicles in the pilot scheme. The complete system has been operational since January 1994.

The Stopwatch project is monitored to analyze the effects of this telematics technology on bus use. In August 1993 (four months before the introduction of Stopwatch) and in October 1994 (with Stopwatch in operation for 9 months) a questionnaire survey was held among bus users. On both occasions respondents at a number of bus stops were interviewed with almost identical questionnaires.

The main conclusions from the statistical analysis of the resulting data sets are (BATT, 1995):

- (1) The increase in bus use attributable to Stopwatch is an estimated 5%. Besides that, some 24% of the respondents in the 'after' survey were new bus users, that is, they had never used the bus before on this route. It is not clear to what extent the generation of this bus use can be attributed to Stopwatch. Definitely not all 24% will be a reaction to Stopwatch, but there is no reason to assume that Stopwatch did not contribute at all.
- (2) Stopwatch contributes to the appreciation of bus use: the level of satisfaction with the product 'bus' has generally increased since the introduction of Stopwatch.
- (3) The appreciation was greatest for young students or young employed. These groups also showed the largest increases in bus use.

<sup>(5)</sup> This was a cross-European initiative led by Hampshire County Council with support from the UK Department of Transport and the European Commission's Transport Telematics Programme (DRIVE II, 1992–1994). For further details on SCOPE, see BATT (1995).



For further results from this questionnaire we refer to the findings reported to DRIVE II (see BATT, 1995). The conclusions cited here illustrate three points which are important for our purposes:

- (1) The technology does indeed lead to an increase in bus use.
- (2) Besides the direct effects discussed in section 2, the indirect effect of improved quality and reliability of the bus service is likely to have a lasting effect which may be much more important in the long run.
- (3) The analysis should take into consideration socioeconomic characteristics of the users.

## 4 Empirical results

### 4.1 Some preliminary remarks

The analysis of section 2 led to two relations that can be investigated with the data from the Stopwatch project. The first result, following from the analysis of uncertainty reduction, predicts that the effect of Stopwatch will be larger when:

- (a) the uncertainty of arrival times is greater;
- (b) the cost attached to this uncertainty is larger;
- (c) the modal-split point is closer to the mode of the distribution which describes the difference in fixed cost of the trips involved.

The second result, following from an improved choice situation at the bus stop, predicts a unimodal relation between the increase of bus use due to Stopwatch and the value of time, with a maximum at intermediate values. Both relations will be investigated here.

The dependent variable to be used below is a binary variable  $y$ , where a value of 1 indicates an increase in bus use due to the introduction of Stopwatch. The model analyzed in section 2 predicts unequivocally no decrease in willingness to use the bus. Therefore, the binary variable measures whether this increased willingness to use the bus is large enough to induce an observable (expected) increase in bus use. For the analysis we use the familiar logit model.

### 4.2 Uncertainty reduction

The effect of Stopwatch on bus use as a result of uncertainty reduction depends on the three factors mentioned above. These factors are operationalized as follows.

The uncertainty of arrival times is represented by a variable *FREQ*, which gives the inverse of the frequencies of the bus service—that is, the interarrival times—as reported by the respondent.<sup>(6)</sup> Missing values for the variable were interpreted as an absence of knowledge, that is, maximal uncertainty, and for practical reasons they were given the value 120 (a bus arrives each 120 minutes), which is twice the largest observed value for the variable. In the estimation a positive coefficient is expected.

A second variable representing uncertainty is the timetable knowledge, *TTK*, of the respondent. It is assumed that such knowledge reduces the uncertainty and given the definition of the variable—implying that more knowledge is represented by smaller values—a positive coefficient is expected.<sup>(7)</sup>

<sup>(6)</sup> No information is given about the punctuality of various bus services, which would be the more relevant proxy for uncertainty. Consequently, interarrival times can be used to reflect uncertainty, basically because a small interarrival time leaves fewer possible outcomes. For example, an interarrival time of 2 minutes practically prohibits a waiting time of, say, more than 5 minutes, whereas an interarrival time of 10 minutes makes a waiting time of 5 minutes not impossible. This shows that interarrival times can be used as a measure of uncertainty, when no further information on the probability distribution is available.

<sup>(7)</sup> The variable for timetable knowledge assumes three values: 1 for those who do have knowledge, 2 for those who just know the frequencies of the buses running, and 3 for those who have no timetable knowledge.



The attitude towards uncertainty is measured by the relative importance attached by the respondents to time-related features of the bus service. The survey contained a question in which the respondent was asked to indicate the importance of six features (measured on a scale from 1: unimportant to 5: very important), three of which were related to arrival times. The ratio of the scores on the time-related features to the sum of the scores on all features is used as the variable *IMPTF*, thus measuring the relative importance of time-related features. A positive coefficient is expected.

Assuming a unimodal function for the distribution of  $F_a - F_b$ , for example, a normal distribution function [compare figure 1(c)] implies that the increase in bus use is largest for respondents with an *ms* point close to the mode, and smallest for respondents with an *ms* point in the tails. This means that respondents with about an equal share of bus and car trips are expected to indicate most often an increase, and respondents with a clear preference for either of the two modes are expected to show a smaller increase. The difference between two categorical variables, measuring the use of bus and the use of alternatives on the route, respectively,<sup>(8)</sup> is defined as the variable *SHAREBUS*, which is included both as a linear and as a quadratic term in the estimation, accounting for the predicted unimodal relationship. So, for the quadratic term a negative coefficient is expected, whereas the linear term may assume either sign.

These variables were used in the logit estimation of the Stopwatch effect, for both the 'before' and the 'after' survey. The 'after' survey in addition offered the opportunity to include a variable which measured the perceived accuracy of the Stopwatch information, *ACCURACY*. The larger this accuracy, the larger the reduction in uncertainty, and the larger the effect of Stopwatch according to the model. Because accuracy is measured by its opposite, the deviance of the Stopwatch time from the realized arrival time, a negative coefficient is expected.

The results of the estimations are given in the first columns of table 1 (see over) where the age and gender of the respondent are included as control variables. The estimations are moderately successful. For the 'before' data all coefficients have the expected sign (though most are not significant), and the location of the optimum with respect to the variable *SHAREBUS* at 0.82 (that is, at a value which indicates only a slightly larger share for bus) is reasonable. The improvement in likelihood is for the most part attributable to the control parameters, but the improvement due to the model is also significant.

For the 'after' data only two variables have the expected sign, including the variable *ACCURACY* which was not included in the 'before' estimation. Again the improvement in likelihood is significant, and in this case the largest part is due to the model parameters. If we compare the 'before' and 'after' results, only one parameter has the correct sign in both cases. The results for the control parameters give a reasonably similar pattern as far as age is concerned, but the gender parameter changes sign.

An explanation for these observations may be that the respondents a priori largely overestimate the accuracy of the system, and hence react strongly and in line with the model. When the technology is working, beliefs about the effect are replaced by experience and the effect of the measure is strongly related to the perceived reduction of uncertainty. It thus appears that the respondents in the 'before' study were not entirely adequately informed on the expected or plausible effects of the Stopwatch project.

#### 4.3 Improved bus choice at the stop

Improvement of the bus choice at the bus stop was shown to be critically dependent on the time preference of the respondent. The available data set gives no explicit

<sup>(8)</sup> For both variables the same categories were defined, namely 1: more than 4 times a week; 2: 1 to 3 times a week; 3: 1 to 3 times a month; 4: less than once a month; 5: never used before.



**Table 1.** Stopwatch effect for partial and full model.

Variable	Uncertainty reduction				Improved bus choice at stop			
	before		after		before		after	
	est.	SE	est.	SE	est.	SE	est.	SE
Constant	-2.42	0.75**	3.14	3.14	-1.79	0.40**	-4.07	0.88**
Male	-0.29	0.15*	0.13	0.29	-0.26	0.15*	0.14	0.29
Age								
25-34	-0.24	0.21	-0.15	0.40	-0.26	0.21	-0.22	0.39
35-44	-0.60	0.24**	-0.59	0.45	-0.60	0.24**	-0.54	0.44
45-59	-0.32	0.21	-1.44	0.62**	-0.39	0.21*	-1.66	0.62**
60+	-1.21	0.22**	-0.77	0.43*	-1.30	0.21**	-0.88	0.42**
FREQ	0.001	0.003	-0.045	0.025*				
TTK	0.27	0.085**	-4.97	2.49*				
IMPTF	1.70	1.38	2.67	2.28				
SHAREBUS	-0.018	0.050	0.074	0.10				
(SHAREBUS) <sup>2</sup>	-0.011	0.016	0.010	0.038				
ACCURACY			-0.65	0.16**				
EWT					0.14	0.09	0.40	0.20**
(EWT) <sup>2</sup>					-0.006	0.005	-0.023	0.011**
Number of observations	1494		1250		1494		1250	
Log-likelihood	-628.20		-199.18		-634.23		-212.49	
Log-likelihood (c)	-637.91		-215.18		-637.91		-215.18	
Log-likelihood (0)	-660.11		-222.48					
LRT (c)	19.42**		32.02**		7.37**		5.39*	
LRT (0)	63.81**		46.61**		51.76**		19.98**	

\* Significant at 10% level; \*\* significant at 5% level.

Note: The dependent variable, the Stopwatch effect, is 1 if the respondent reports an (expected) increase in bus use due to the introduction of Stopwatch. Est. means estimate of the variable; SE means standard error of the estimate; Log-likelihood is the log-likelihood at the optimum; Log-likelihood (c) is the log-likelihood when only the control variables (age and gender) are included; Log-likelihood (0) is the log-likelihood when only the constant is included. The likelihood ratio test statistics (LRT) are similarly defined.

information on time preferences of travellers. Therefore, approximate variables have to be used.

The proxy we use is expected waiting time (EWT) which is the time travellers expect to wait until the bus they intend to take arrives, *from the moment they arrive at the bus stop*. The idea is that people with high time preferences will minimize their expected waiting time, whereas people with low time preferences will not care very much about waiting and hence will have longer waiting times on average. Thus, a monotonic negative relation between expected waiting time and time value may be postulated.<sup>(9)</sup> EWT is measured in minutes when waiting time is 10 minutes or less, and a residual category 'more than 10 minutes'. For estimation purposes, this last category is set to 15 minutes.<sup>(10)</sup>

<sup>(9)</sup> Other proxy variables we used (destination of the trip, occupation of the respondent) gave far less satisfactory results.

<sup>(10)</sup> This is justified by the observation that the majority of the respondents report waiting times of either 5 or 10 minutes. A similar tendency of reporting multiples of 5 minutes was observed by Small (1982). These values seem to be readily 'available' in the respondent's mind when such a question is asked. Thus, it is reasonable to assume that a similar internal value (15 minutes) is a reasonable guess, when waiting time exceeds 10 minutes (compare Tversky and Kahneman, 1982). See Small (1982) for a different treatment.



Variable	Combined effects			
	before		after	
	est.	SE	est.	SE
Constant	-2.97	0.83**	1.67	3.21
Male	-0.29	0.15*	-0.11	0.30
Age				
25-34	-0.22	0.21	-0.13	0.40
35-44	-0.60	0.24**	-0.57	0.45
45-59	-0.31	0.21	-1.41	0.62**
60+	-1.21	0.22**	-0.70	0.43*
FREQ	0.001	0.003	-0.046	0.025*
TTK	0.24	0.086**	-5.15	2.51**
IMPTF	1.71	1.38	2.68	2.29
SHAREBUS	-0.016	0.050	0.072	0.10
(SHAREBUS) <sup>2</sup>	-0.011	0.016	0.011	0.038
ACCURACY			-0.67	0.16**
EWT	0.13	0.09	0.44	0.20**
(EWT) <sup>2</sup>	-0.006	0.005	-0.025	0.011**
Number of observations	1494		1250	
Log-likelihood	-626.43		-196.45	
Log-likelihood (c)	-637.91		-215.18	
Log-likelihood (0)				
LRT (c)		22.96**		37.46**
LRT (0)		67.36**		52.06**

The middle columns of table 1 give the estimations, with the same control variables included as above. The estimation is again moderately successful. The EWT variables have the correct signs that lead to a maximum probability of increased bus use for some positive value of EWT, namely 12 minutes in the 'before' sample, and 9 minutes in the 'after' sample, which are reasonable values in light of the range of EWT. In addition, the increases in the likelihood are again significant. In this case there are no important differences between the 'before' and the 'after' sample results.

#### 4.4 Combined effects

When both model elements are included simultaneously (see the last two columns of table 1) we find that most results are not substantially affected. A comparison of the increases in likelihoods, however, reveals that the effect attributable to uncertainty reduction is larger than the effect of the improved bus choice at the bus stop. This holds for both the 'before' and 'after' data. This observation suggests that uncertainty reduction is the most important effect of the Stopwatch technology.



## 5 Conclusions and discussion

Information technology can indeed help in increasing public transport use, that is, getting people out of their cars and onto the bus. In this paper we have modelled two incentives for this modal change—the reduction of uncertainty at the bus stop and the improved optimality of bus choice at the stop—and pointed to a third reason, the general increase in perceived quality of the service.

According to the model, information technology can lead only to a nondecrease in bus use. This can be regarded as a specification of the general result that (free) information always leads to better choices and therefore to increases in utility (for example, see Marschak, 1974). The empirical analysis based on the model basically investigated whether the potential increase in utility would be sufficient to produce an actual change in modes. This empirical analysis proved the relevance of the model, as most hypotheses derived from the theory were not rejected despite the fact that proxy variables had to be used. It also suggested that from the two incentives distinguished, the effect of uncertainty reduction was the more important.

Thus, we have demonstrated the potential effect of information technologies in generating increases in bus use, both theoretically and empirically. The size of the effect needs to be investigated further but is likely to range from small (5%) to substantial (over 20%). Average users and people with intermediate time preferences are expected to profit most from such technologies, while in particular the elderly do not seem to be very interested. So, policy initiatives to stimulate further bus use on the basis of information technologies should be directed to the younger generation such as students and (young) professionals.

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**APPENDIX**

It is evident that  $t_e^*$  depends on  $\alpha$ . Here we will support our conjecture that this relation is positive, that is, that  $t_e^*$  increases when  $\alpha$  increases. The argument is as follows. First,  $t_e^*$  is the solution of the equation [assuming that this solution exists, see footnote (2) in the text]:

$$F_c + \alpha \int_{t_e^*}^{\infty} t_c h_c(t_c | t_c > t_e^*) dt_c = F_e + \alpha t_e^*. \tag{A1}$$

Solving this equation will in general not lead to a closed-form solution for  $t_e^*$ , depending on the distribution function which is used. However, equation (A1) can be formulated as an implicit function

$$G(t_e, \alpha) = \frac{F_e - F_c}{\alpha} + t_e - \int_{t_e}^{\infty} t_c h_c(t_c | t_c > t_e) dt_c = 0. \tag{A2}$$

and the solution  $t_e^*$  is then a function of  $\alpha$ ,

$$G[t_e^*(\alpha), \alpha] = 0. \tag{A3}$$

This allows for the application of the implicit function theorem which says

$$\frac{\partial t_e^*}{\partial \alpha} = - \frac{\partial G}{\partial \alpha} / \frac{\partial G}{\partial t_e^*}. \tag{A4}$$

Now  $\partial G / \partial \alpha$  is

$$\frac{\partial G}{\partial \alpha} = - \frac{\Delta F}{\alpha^2}, \tag{A5}$$

where  $\Delta F = F_e - F_c$ . Thus, by definition  $\Delta F > 0$ , and expression (A5) is unequivocally negative. The determination of the sign of  $\partial G / \partial t_e^*$  is, however, much more complicated. Writing  $H_c$  for the cumulative distribution function of  $t_c$ , we find

$$\begin{aligned} \frac{\partial G}{\partial t_e^*} &= \frac{\partial}{\partial t_e^*} \left[ t_e^* - \frac{1}{1 - H_c(t_e^*)} \int_{t_e^*}^{\infty} t_c h_c(t_c) dt_c \right] \\ &= 1 + \frac{[1 - H_c(t_e^*)] t_e^* h_c(t_e^*)}{[1 - H_c(t_e^*)]^2} \int_{t_e^*}^{\infty} t_c h_c(t_c) dt_c. \end{aligned} \tag{A6}$$

After some rearranging this gives

$$\frac{\partial G}{\partial t_e^*} = 1 + \frac{h_c(t_e^*)}{[1 - H_c(t_e^*)]^2} \int_{t_e^*}^{\infty} (t_e^* - t_c) h_c(t_c) dt_c. \tag{A7}$$

Clearly, the integral in equation (A7) is negative as the integrand is negative, because  $t_c > t_e^*$ . It is, however, conjectured that under certain conditions (for example, log-concavity) the entire expression is positive; in other words, that the integral multiplied by the density in  $t_e^*$  and divided by the square of the probability mass right of  $t_e^*$  is larger than  $-1$ . Given the correctness of this conjecture  $\partial G / \partial t_e^*$  is positive, and this in combination with the negativeness of expression (A5) proves that  $\partial t_e^* / \partial \alpha > 0$  because of expression (A4).

The conjecture is easily affirmed when a uniform distribution over the interval  $[0, k_c]$  is assumed for  $h_c$ . The inequality can also be proven for normal distributions. For a standard normal distribution we know the expression for the expectation of a truncated variable ( $x > c$ ) to be (see Maddala, 1983):

$$E(x | x > c) = \frac{\phi(c)}{1 - \Phi(c)} = M(c).$$



Differentiating this with respect to  $c$  gives

$$\frac{\partial M}{\partial c} = -\frac{c\phi(c)}{1-\Phi(c)} + \frac{\phi(c)\phi(c)}{1-\Phi(c)^2} = M^2 - Mc.$$

The variance of a truncated normal variable is known to be

$$\text{var}(x|x > c) = 1 - M(M - c).$$

Thus, the variance is 1 minus a term which is identical to the derivative of the expectation. But because the variance is by definition positive, it follows immediately that this derivative is less than 1, which was to be proven. As could be expected an analogue proof also holds for normal distributions in general.

Notice that a consequence of this proof is that if a solution  $t_c^*$  exists for normal distributions it also is unique [see footnote (2)]. Rewriting expression (A2)—implementing the normal distribution—as:

$$\alpha = \frac{\Delta F[1 - \Phi(t_c)]}{t_c - \phi(t_c)},$$

we find that  $\alpha$  is monotonically decreasing in  $t_c$ . Therefore the function described by equation (A8) is one-to-one, and hence a solution, if it exists, is unique, and this also holds for the inverse function.

In general (that is, without imposing ‘certain condition’) the inequality cannot be proven, however. In particular, for an exponential distribution with mean  $1/d$ , the truncated mean is  $t_c^* + 1/d$ . This leaves equation (A1) independent of  $t_c$  and hence  $\partial t_c^*/\partial \alpha = 0$ . This suggests, however, that  $\partial t_c^*/\partial \alpha$  is nonnegative instead of strictly positive. Although this is less convincing, it would not really frustrate the argument in the text.<sup>(11)</sup>

<sup>(11)</sup> We wish to thank one anonymous referee for making some useful and challenging comments on the points raised in this appendix.