How Much Disruption to Activities Could Fuel Shortages Cause? - The British Fuel Crisis of September 2000

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Abstract

In September of 2000 the UK experienced a blockade of oil refineries in response to rising fuel prices. These protests resulted in severe fuel supply disruptions that intensified over the course of about one week. During the peak of the crisis, travel activity by car was curtailed. This paper analyzes survey data collected about two months after the crisis utilizing the recent memory of respondents as to how they would expect this sort of disruption to affect their participation in daily activities. Specifically, we focused on a variety of non-discretionary and discretionary activities and examined what factors are associated with respondents expecting disruption to those activities. Statistical models were developed to analyze how demographic factors, commute mode selection, vehicle characteristics, and various other factors can explain how individuals expect disruption to their activities. Results suggest that the majority of individuals do not expect major disruptions, although for more car-dependent individuals, disruption was expected to be substantial, especially for work-related trips. These results have implications for the potential success and benefits of an integrated transport policy.

Introduction

In September of 2000 rising gasoline prices in several European countries sparked protests and demonstrations. In the UK these protests resulted in blockades of oil refineries preventing the distribution of petroleum products to gasoline stations. This resulted in a temporary disruption to gasoline supplies that was exacerbated as consumers hoarded gasoline supplies, quickly resulting in severe supply shortages. While the crisis lasted only about a week, it provided an opportunity to study how transport behavior is affected and how people's perception of their ability to engage in various activities could be affected by more severe disruptions.

An understanding of these issues is of interest to policy makers and transport planners primarily because it provides a test of the feasibility of many government policies that seek to reduce vehicle usage (Bonsall, 2002). UK government policy explicitly seeks to reduce vehicle usage and increase the use of public transport and non-motorized modes of travel. Our results are revealing in suggesting that achievement of these goals could be a difficult proposition given existing levels of dependency on the private car.

In addition, these type of disruptions to the transport system are of interest to the behavioral researcher because they may expose the limits of behavioral response and adaptation in a way that more typical, and marginal, changes in the transport system do not. The most notable recent examples of such coercive changes to transport supply were the earthquakes that took place in the Northridge area of Los Angeles in 1994 and in the Hanshin-Awaji (Osaka-Kobe) region of Japan in 1995 (see, Chang and Nojima, 2001) (both of which caused substantial and widespread disruption) and the public transport strike in the Paris region in 1995.

This paper analyzes these behavioral adaptations by examining how individuals and households believe expected disruptions would affect various activities that they engage in.

While the disruption was a temporary event, this information allows us to better understand what options people have to access activities in the absence of motor vehicles given existing spatial development patterns and public transport systems.

As part of this project a series of three focus groups were held to obtain qualitative information on how people responded to the supply disruptions. This provided us with information to design a telephone survey that was administered by MORI about two months after the crisis was over. This paper reports on our quantitative findings from the survey. Polak et al. (2001) report in more detail the qualitative findings from the focus groups.

Our analyses builds upon prior research in this area. We begin with a brief review of this literature in the next section . This is followed by the theoretical basis for this work, much of which is grounded in studies of how activities drive transport behavior. The data collected for this study is then described followed by an analyses. We conclude with some overall comments on the implications for transport policy.

Previous Literature

The Northridge earthquake

The 1994 Northridge earthquake in Los Angeles, California, caused the closure of two major freeways and damage to the arterial network. Many shops and businesses also suffered damage and were closed. The impacts of the earthquake on travel behavior were studied by Boarnet (1998), Giuliano and Golob (1998) and Gordon *et al*. (1998).

Giuliano and Golob (1998) found that travellers were more likely to change route than mode. Despite this, commuter rail usage increased from about 0.2 percent of travel in the I-5 corridor to nearly 10 percent in the first week after the earthquake. This share quickly diminished to about 2 percent several weeks after the earthquake. Interestingly, five months later in June 1994, commuter rail's share was still four times previous totals, though the authors point out that this may be due to the opening of new stations, increased frequency and various network extensions which opened during this time. Arterial traffic volumes also remained higher after the reopening of the freeway suggesting that some travellers preferred new routes that they found in response to the network disruption.

Giuliano and Golob (1998) also report results from a survey conducted in February 1994 to measure changes in commuter travel in response to the earthquake. The data collected was geo-coded to separate the sample into groups near the two effected corridors and those elsewhere in the region. Departure time changes to leave home earlier (about 20% of respondents) and route changes (about 30%) were the two largest responses found. This was compared with much smaller changes in their control sample. Gordon *et al.* (1998) conducted a survey that found similar changes in departure time and route choice. About 5 percent of respondents in the I-5 corridor also reported that they changed their home or work location. This was a larger amount than those reporting either a change of mode or work schedule and it is likely that many of these relocation decisions may not have been in response to the earthquake but represented normal relocations. The lack of mode choice changes in the work trip survey suggests that reductions in total trips (measured by screenline counts) were due mainly to discretionary non-work trips. This was confirmed by other surveys including that of Gordon *et al*. (1998) which found a decrease in the frequency of grocery shopping (from 2.2 to 1.7 times a week).

Giuliano and Golob (1998) conclude that travellers are very flexible to short-term disruptions and make adjustments, primarily through rescheduling and route choice. However, the evidence from Northridge suggests that travellers also quickly return to their pre-disruption behavior when transport conditions are returned to normal.

The Hanshin-Awaji (Osaka-Kobe) earthquake

The Hanshin-Awaji earthquake that occurred in January 1995 was much more extensive and devastating in its effects than Northridge. It claimed a total of over 5,300 lives and led to the closure of 27 major highways and all rail lines in the Osaka-Kobe corridor as well as causing severe damage to the urban infrastructure throughout the region. Kitamura *et al*. (1998) summarize a number of studies that investigated the impact of the earthquake on traffic and travel behavior.

The analysis of data on aggregate traffic flows before and after the earthquake indicated that about a month after the earthquake (by which time most key roads had been returned to operation) flows on roads outside the Osaka-Kobe corridor had resumed their pre-quake levels, yet traffic volumes on roads in the Osaka-Kobe corridor were still substantially below their pre-quake levels.

Further analysis of a variety of disaggregate data sources suggested that even five months after the earthquake (by which time most of the damaged network had been at least partially restored) the mobility of residents in the Osaka-Kobe corridor was still reduced relative to those elsewhere and that this reduction could be attributed to the combination of a small reduction in daily trip rate (-0.5), significantly reduced non-work travel (in terms of both frequency and distance) and a substantial reduction in the range of destinations visited for non-work activities.

The Paris region public transport strike

Another form of disruption occurred in 1995 in the Paris region when a public transport strike broke out that lasted for three weeks (Coindet, 1998).

A survey conducted shortly after the end of the strike attempted to measure behavioral responses that had taken place. It was found that there were large shifts in departure times for work trips done by car (up to one and a half hours earlier). Other modes, such as bicycling, walking, and carpooling also increased, but did not see any long term increases in usage after the strike ended. Coindet (1998) concluded that economic activity within Paris did not suffer greatly because of the strike, though there were large increases in average commute times.

Limitations and implications

In interpreting the evidence of these and related studies we must bear in mind that there are considerable methodological difficulties associated with drawing inferences about behavioral responses in such situations (e.g., difficulty in achieving representative samples, in establishing valid controls against which comparisons can be made and in correctly attributing the source of observed change to the transport disruptions in question). Nevertheless, some general patterns do seem to emerge.

These studies suggest that when faced with major disruptions in transport supply, individuals typically respond with modifications to the route and timing of work-related travel (and to a lesser degree by changing mode) and with a reduction in the frequency of non-work activities. As part of these processes of adaptation, travellers seem able to absorb (at least in the short term) considerable increases in travel times. It appears that most of these modifications are reversed when normal supply conditions are restored. However, the evidence from Hanshin-Awaji in particular (where supply disruptions were most extreme and long lasting) suggests that the impacts on non-work travel may be more persistent, with the altered behaviors continuing even after the original disruptions have abated.

These conclusions suggested a number of specific research questions that served as the objectives of the current study. This paper focuses on the analyses of individual's ability to engage in various work and non-work activities under disruptive conditions. The underlying factors that affected both the level of disruption that individuals faced and their ability to adapt are investigated.

Theoretical Background

Travel behavior is dependent upon the activities that people engage in. From this perspective, demand for travel is derived from the demand to access these other activities.

Normally one would expect choices to be based on a minimization of the generalized costs of travel in the context of the maximization of the benefits derived from the activity pursued.

The fuel shortages caused disruption to both the feasibility of travel by private cars and, in some cases, the availability of economic activities. Clearly, as people anticipated running out of fuel they would be expected to curtail some discretionary travel. This could include recreational travel, shopping trips, and even visits to health care providers. In some cases, these would be accessible by alternative modes. However, a further constraint to activity participation under these conditions was the ability for economic activities to continue, for example, if a shopkeeper cannot get to work or a doctor cannot get to the hospital.[1] Shortly before the fuel crisis ended there were fears that the bus system would run out of fuel.

Disruption to trips and activities is therefore expected to be more likely for those dependent on motorized forms of transport, especially private cars. In addition, those that tend to travel greater distances to work by car and consume relatively more fuel would tend to run out faster. They may also be less able to use public transport for these trips, such as a long commute by car. The types of activities disrupted would depend on the relative availability of other modes for accessing those activities. The analysis presented below seeks to examine some of these questions by examining how people expect future fuel shortages to disrupt their participation in certain activities.

Data Collected and Preliminary Analyses

One of our objectives in conducting this study was to collect data while the fuel crisis was still fresh in people's minds. This allowed us to ask questions both on what people actually

[1] Some people whose jobs were designated as essential were able to receive emergency supplies of fuel.

did during the crisis and also ask hypothetical questions concerning possible responses should another (more serious) crisis occur in the near future.[2]

For the collection of data, telephone interviews were conducted by MORI, filtered by car access and selected randomly from across London, the South East and North East of England and representing a range of urban, suburban, and rural settings. The interview, which lasted about 8 minutes, had two parts; the first related to actual responses to the fuel crisis, while the second related to stated responses to a hypothetical fuel shortage sometime in the future. Information on normal commuting activity and demographic data was also collected. We collected data on 1001 respondents.

The sample collected probably over-represented those who are relatively more car dependent. The national average miles driven per licensed driver is about 9000 miles per year (DETR, 2000). Our sample had an average reported miles driven of about 15000 miles per year. This over-representation could have occurred since those who are more car dependent may have been more interested in answering the survey questions, whereas those who declined may have been less car dependent. In any case, we do not see this as a problem since we are interested in seeing how people expect to be disrupted by possible fuel shortages and more car dependent people would be expected to experience greater levels of disruption. In short, we are probably analyzing slightly more car dependent individuals than the typical Briton.

Of those sampled, 29% ran out of fuel during the fuel crisis or had insufficient fuel to make their normal journeys. Only 15% had access to emergency fuel supplies. The majority of respondents (71%) were working, 4% were either attending school or college, and the remainder (25%) did neither. 55% of respondents had access to one car, 37% to two cars, 7%

[2] This was not a hypothetical possibility, as the fuel protestors were threatening future blockades at the time the survey was conducted, about two months after the crisis occurred.

to three cars and 1% to four or more cars. 6% of respondents lived in households with access to a motorcycle.

Table 1 shows the change in mode choice before and during the fuel crisis for all respondents. The biggest proportionate increase is for car as passenger (60%) followed by public transport (50%) which also had the largest absolute increase (44 respondents). The nature of these modal shifts is also analyzed in Table 1. Of 582 respondents who chose car as driver before the fuel crisis, 422 (73%) remained with the car as driver, 50 (9%) chose public transport, 30 (5%) walked and 20 (3%) went by car as passenger. Interestingly, of 88 respondents who went by public transport before the crisis, 9 (10%) switched to car as driver, so the proportionate switch between these two modes was about equal. While our questionnaire did not ask why people switched mode, two possibilities suggest themselves. Reduced road congestion and over-crowding on public transport may have caused those with adequate fuel reserves to drive instead of taking public transport. Alternatively, there may have been a perception that public transport providers were low on fuel and could not offer reliable service.[3]

Of those respondents who continued to drive to work, school or college during the fuel crisis, 402 used the same car and 24 used a more fuel-efficient car, possibly reflecting the limited scope in practice for people to swap between alternative vehicles (at least in the short run).

Clearly, there were behavioral adaptations for various trips during the fuel crisis. To understand some of these effects more clearly we conducted a multivariate analysis. The method used is described in the next section followed by a presentation of the results.

[3] To our knowledge no public transport providers ran out of fuel, though by the end of the crisis some were nearly out of fuel. Reliability could have been affected if drivers or other public transport employees could not drive to work.

Methodology

As part of our telephone survey of those with regular access to a private car, we included one question that elicited information on the expected disruption to various activities if respondents were faced with another fuel shortage (Figure 1). This question elicited a scaled response ranging from 1 to 5. A higher score reflected severe disruption while a low score reflected none at all. It was assumed that people's experience with the recent fuel crisis would allow them to better understand how their access to activities could be disrupted if a similar situation were to occur.

We analyzed each individual component of the score, comprising eight different questions related to expected disruption (as shown in Figure 1). Since the scaling of each response is ordinal in nature no judgments can be made as to the relative cardinal representation of the answers. For example, a respondent answering with a "5" does not imply that the response reflects a situation 5 times more disruptive than someone answering with a "1". For this reason, we use an ordered probit model to estimate the statistical significance of various parameters for each of the individual questions.

Ordered probit models allow the estimation of a model,

$$y_i^* \; ? \; ?' x_i \; ? \; ?_i$$

where the dependent variable, y_i*, is an underlying continuous variable measured on an ordinal scale (McKelvey & Zavoina, 1975; Long, 1997).[4] A vector of independent variables, x_i, coefficient estimates, $?$, and an error term, $?_i \sim N?0,? ?$, are estimated using maximum likelihood. Threshold values, $??\,?$, are also estimated and are related to the ordinal values of the dependent variable as,

$$y \; ? \; 0 \quad if \quad y^* \; ? \; 0$$

[4] Applied studies in transport that have used this method include Abdel-Aty (2001) in a study of transit ridership, Kockelman & Kweon (2002) for injury severity, Agyemang-Duah et al. (1995) and Agyemang-Duah & Hall (1997) for trip generation, Bhat & Pulugurta (1998) for number of vehicles owned in a car ownership model, and Bhat (1999) in a study of evening commute trip chaining.

$$y ? 1 \quad if \quad 0 ? y^{*} ? ?_{1}$$

$$y ? 2 \quad if \quad ?_{1} ? y^{*} ? ?_{2}$$

$$\vdots$$

$$y ? J \quad if \quad ?_{J?1} ? y^{*}$$

When a constant term is estimated it cannot be distinguished from one of the thresholds and thus in our estimates with five choices we have three threshold values.

The predicted probabilities for each ordinal outcome can be calculated

$$\Pr(y ? m \mid \boldsymbol{X_i}) ? F(\hat{?}_m ? \boldsymbol{X_i}\hat{\boldsymbol{ß}}) ? F(\hat{?}_{m?1} ? \boldsymbol{X_i}\hat{\boldsymbol{ß}}) \qquad (6)$$

Calculation of these probabilities allows a better understanding of the relative effect of the independent variables. These results are calculated and discussed in the next section. The *ß* values in ordered probit models do not provide marginal effects. In the discussion that follows, we focus on whether the effects are statistically significant and also on the change in the predicted probabilities relative to a reference case.

Results of Analyses

In discussing our analyses of responses to the question on expected disruption in Figure 1, we can identify two general categories of activities. These are non-discretionary activities that must be conducted on a regular basis and discretionary activities that can often be postponed or cancelled. The first consist primarily of work and school trips. The second include recreational activities and visits to doctors or health care providers. Shopping trips are also included and could be considered non-discretionary in many cases, although food shopping trips would probably have to occur on a more regular basis.

Table 2 displays the distribution of the categorical answers for the question in Figure 1 on expected disruption. As can be seen, work-related trips tend to have one of the highest levels of expected disruption with over 35% of respondents being disrupted, but also have a large number of individuals who did not expect these trips to be disrupted (about 30% for commuting trips and 36% for work-related travel). A similar result can be seen for visiting friends and family, which would be considered a more discretionary trip. On the other hand, responses to the other questions had a large number of people who were not affected. While these are primarily discretionary trips, taking children to school and going to the shops also had relatively fewer people expecting that these activities would be disrupted.

Much of our analyses of these variables is essentially exploratory. In general we have few expectations of what factors may determine the level of expected disruption to trips. In general, we hypothesize that those who commute by car, higher income households, those with more motorized vehicles, those with less fuel efficient vehicles, and those living outside London would expect more disruption. We also expect that non-discretionary activities would generally be subject to greater levels of disruption. As our discussion (below) shows, we do not find evidence to support the majority of these hypotheses.

The analysis includes a discussion of the statistical significance of the independent variables included in the models (shown in Table 3). In addition, we analyzed the choice probabilities which allow us to determine how the dependent variable can change with changes in the independent variables. The probability scores (shown in Table 4) were calculated for the choice of answering 4 and 5 (relatively more disruption) and answering 1 and 2 (relatively less or no disruption). The change in the probability scores are compared to the probability scores for a reference individual defined by the parameters in Table 5. This allows us to see how changing each of the independent variables (as shown in Table 5) will affect the dependent variable.

Non-discretionary Work-related Trips

The first column in Table 3 displays results for expected disruption to commute trips (to work, school or college). The results clearly show that those using motorized vehicles expect disruption to their trips while those using non-motorized modes do not. Not surprisingly, those who actually ran out of fuel expect future commute trips to be disrupted if fuel runs out.

Survey respondents were asked the size of their vehicle's engine. Responses were elicited for each vehicle owned using pre-determined categories of engine capacity. The first vehicle for which the engine capacity was given has been included in our models on the assumption that this is the household's primary vehicle. Our results show that as engine size increases, implying less fuel efficiency, the level of expected disruption increases (at the 90% confidence level for commute trips). This is not surprising and implies that a more fuel efficient fleet would limit the disruption to travel patterns caused by fuel shortages.

Age is also a statistically significant factor, with older respondents expecting less disruption. It is unclear why this is the case but may simply reflect fewer work commitments. Income levels were not found to be significant for expected disruption to commute trips, nor were any of the regional dummy variables.

Probability scores for severe disruption (4 and 5) associated with the expected disruption of commuting show a large change for those who use a motorized mode for commuting to work (0.4994 compared to 0.1997 in the reference case). Those using non-motorized modes show a very low probability of severe disruption (0.0149). Interestingly, variation in age has only a small effect on the probability scores despite having a statistically significant effect (changing to 0.2410).

'Travelling as part of work' was assumed to be the actual travel conducted while a respondent was working. Over 400 usable responses to this question were recorded which seems relatively high. It is possible, therefore, that some individuals misinterpreted this question. The results are broadly similar to those for commute trips with the exception that higher income individuals have a statistically significant coefficient. This may simply indicate that higher income individuals are more likely to travel as part of their job. Surprisingly, car commuters do not have a statistically significant coefficient.

Probability changes associated with this model show that overall changes are relatively small. The reference case has a relatively high (0.5640) expectation of severe disruption. The largest reduction in this probability value is associated with those using non-motorized modes (0.2370). Changes due to age, income, and engine capacity are all relatively minor.

In general, most of the effects associated with non-discretionary work-related trips are relatively minor. Surprisingly, the regional dummy variables did not have any effect. While the overall results suggest that about half the sample expect a large degree of disruption to work-related trips, it is also reassuring that many do not. Our multivariate analyses suggests that those most expecting disruption use a motorized mode to begin with, as well as those who ran out of fuel. Clearly these are people that are relatively more dependent on motorized transport. The constraints that make them more dependent, however, such as lack of public transport, unfortunately cannot be measured with the data available.

Non-discretionary School Trips

For trips to take children to and from school, we found only one significant effect above the 95% confidence level. This was for residents of the South East of England who were less likely to expect disruption to school trips. The probability associated with severe disruption for residents of the South East was only 0.3309 relative to 0.4903 in the reference case. Our expectation would have been that residents of Inner London would experience the least disruption, but the coefficient value for Inner London residents is not statistically significant and even has a positive value. Educational policy in Britain allows relative freedom of choice to select schools outside of one's immediate neighborhood. If Inner

London schools are generally of lower quality (relative to the South East) then residents may be transporting their children over longer distances leading to greater levels of disruption.

Several other variables were significant at the 90% confidence level. This included the number of children under 16 in the household, which was associated with greater disruption. Clearly, the more children living in a household, the more disruption would be expected for these types of trips and the probability of severe disruption increases to 0.5874.

Those who can commute by non-motorized modes also had a 90% level of significance of not expecting disruption to school trips with a large reduction in the probability of severe disruption to 0.1573. As with the work trips, the ability to commute by non-motorized modes seems to allow other trips to be less disrupted. This may simply be representing land use or urban design characteristics that allow trips to be more easily taken by non-motorized modes.

Interestingly, men also did not expect disruption to school trips at nearly a 90% level of significance, compared to women. This may indicate that men are less likely to take children to and from school.

Shopping Trips

As mentioned previously, shopping trips are probably generally discretionary and can be postponed for longer durations, with the exception of food shopping trips. Probability scores suggest relatively less disruption for these trips and 426 respondents said these trips would not be affected by a fuel shortage.

Passengers in cars (for commute trips) have the highest level of not expecting disruption. Perhaps these individuals do not currently use cars for shopping trips. Social classes A and B[5] show the largest probability score associated with disruption (0.3557),

[5] UK National statistics use social class groupings to identify occupational categories. Those definitions are, social class A: professional occupations, B: managerial and technical occupations, C: skilled occupations, D: partly skilled occupations, E: unskilled occupations.

though the change is relatively small compared to other models. Overall, we find few patterns to explain factors underlying expected disruption to shopping trips.

Discretionary Trips

The coefficients in the model for 'visits to friends and families' show a large significant effect for those who commute by all modes, relative to those who work at home (which is the omitted dummy variable). These types of trips might be to destinations not easily served by alternative forms of transport, in addition to being longer than typical commute trips. Higher income households expect less disruption for trips to families and friends, though the change in probability score is minor. This may represent those with higher income moving further away from family and thus these trips would normally be via intercity rail or air transport. Lower income households may have more family connections locally, which would imply they are normally visited by private car. On the other hand, those in social classes A and B expect more disruption (relative to other social classes) at nearly the 90% confidence level. While we don't know the relative distance of most of these types of trips, it is interesting that total vehicle miles traveled is not a significant predictor of expected disruption.

The model for discretionary trips for hobbies and past-times has only one significant variable, which is income. Those with higher income expect less disruption, however the total effect is small with a reduction in the probability score of severe disruption being quite minor. Of all the models, this one does not show a good overall fit as measured by a chi-square test.

The level of expected disruption of trips for taking children to out-of-school activities has significant coefficients on the gender coefficient, total car ownership, and number of children in the household. Households with more children under 16 expect more disruption. Relative to women, men expect less disruption to these trips (perhaps, again, because they make fewer of these trips compared to women). Increased vehicle ownership also leads to more disruption in this model. Those who actually ran out of fuel also are more likely to expect disruption to these types of trips with a 90% significance level.

The level of expected disruption to trips to the doctor or a health care provider appear to have one of the largest amount of respondents not affected by fuel shortages with over 50% not affected (see Table 2). The most significant factors affecting disruption levels appear to be income and the number of motor vehicles owned. The choice of commute mode does not seem to increase levels of expected disruption relative to working at home, having insignificant coefficients for all the modes, including those who commute by car. While not shown in the current model, tests of whether those who are retired are more disrupted for this type of trip did not show a significant effect and age also is not significant. This overall result is quite interesting as it does imply, that at least for our sample, trips to health care providers are unlikely to be disrupted. Perhaps they are considered relatively discretionary or are infrequent enough that they are unlikely to be disrupted.

Summary of Results

While the results for each of the activities considered show a range of different results, we can draw some general conclusions. First, those who are capable of commuting to work by non-motorized modes show less likelihood of disruption for most types of activities (except visiting friends and families). This implies that the ability to commute by a non-motorized mode allows other activities to be undertaken with less concern about fuel supplies. While we can't say for certain, this may be a function of land use and urban design patterns that make non-motorized modes more feasible for commute trips also allowing other travel options for non-work activities.

This is not consistent, however, with the results of our regional dummy variables. Regional effects appear to play no major role in affecting expected levels of disruption. This is quite surprising as we expected that residents of Inner London in particular would expect less disruption to many of their activities, primarily because of the relatively good public transport network and the ability to walk to many destinations.

The main effects related to demographic variation appear to be associated with having children in the home and this appears to mainly affect trips involving children. Men appear less likely to expect disruption to trips associated with children, suggesting that they rely more upon women to conduct these activities (and to deal with any disruption that may occur). Differences in income levels appear to have very minor effects on the probability levels associated with the disruption scores. This is also true of the social class parameters.

Conclusions

One of the primary conclusions of our work is that the majority of activities and individuals in our survey, do not expect a great deal of disruption should another fuel shortage occur. This is most likely a result of the diverse transport systems available in the UK and the relatively compact urban forms. Despite this optimistic conclusion, there are many individuals in our sample who expect severe disruption, especially to work-related trips. Clearly, this is a result of wide-spread dependency on the private car. Only one of the variables that was nearly always associated with less expected disruption was associated with those who commute by non-motorized modes.

This dependency on private vehicle usage suggests that efforts to shift people to other modes of transport will be difficult. However, the ability of many people in our sample to avoid disruption to their activities suggests that there are feasible methods for doing so. While our study did not investigate these issues in detail, the push for an integrated transport system may be one mechanism for moving in this direction. Further increases in fuel prices, however, as a method of discouraging increased motorization may be difficult to achieve given the public response as demonstrated by the fuel blockades (Parkhurst, 2002).

Our results are clearly not conclusive but only a step towards a better understanding of these issues. More research is needed to understand the interactions between discretionary and non-discretionary trip-making. While we don't wish these situations on any region or country, there will undoubtedly be future opportunities to study temporary transport supply disruptions, providing transport researchers an opportunity to better understand how people respond.

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Figure 1
Questions used in survey to elicit expected disruption to trips

We would now like you to consider the impacts on your travel if fuel supplies were to run out tomorrow with some uncertainty as to when your local petrol station would have new supplies available. Using a scale of 1-5 where

1 = Not affected at all,
and
5 = Severe disruption to your trips

please rate how the following types of journeys would be affected? In answering this question, please consider other options, other than the car, that might be possible for making the trips.

Commuting to and from work/school/college
Travelling as part of work
Taking children to and from school
Going to the shops
Visiting friends and family
Hobbies and past-times
Taking children to out-of-school activities or friends
Trips to the doctor or health care provider

Table 1
Mode shifts during the fuel crisis (all respondents)

Before/ During	Car as driver	Car as passenger	Motorcycle	Public transport	Bicycle	Walk	Van or truck	Other	Work from home	Don't know	Did\could not get to work	Unaffected as on holiday	Unemployed during the crisis	TOTAL (before)
Car as Driver	422	20	2	50	13	30	0	5	7	1	12	16	4	582
Car as passenger	1	15	0	4	0	5	0	0	0	0	0	0	0	25
Motorcycle	1	1	4	0	0	0	0	0	0	0	0	0	0	6
Public transport	9	0	0	73	1	4	0	0	0	0	0	1	0	88
Bicycle	2	0	0	1	16	2	0	0	0	0	0	0	0	21
Walk	3	2	0	3	1	68	0	0	0	0	0	1	1	79
Van or truck	0	0	0	0	0	0	4	0	0	0	1	0	0	5
Other	0	2	0	0	0	1	0	0	0	0	0	0	0	3
Work from home	1	0	0	1	0	1	0	1	12	0	0	0	0	16
Don't know	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TOTAL (during)	439	40	6	132	31	111	4	6	19	1	13	18	5	825
Percent change relative to before	-24.57%	60.00%	0.00%	50.00%	47.62%	40.51%	-20.00%	100.00%	18.75%	-	-	-	-	-

Table 2
Distribution of Expected Disruption Scores

Expected Disruption Score	Commuting to and from work/school/college		Travelling as part of work		Taking children to and from school		Going to the shops		Visiting friends and family		Hobbies and past-times		Taking children to out-of-school activities or friends		Trips to the doctor or health care provider	
1 (not affected)	249	29.9%	261	36.5%	325	57.7%	426	43.4%	242	24.4%	391	40.2%	263	43.1%	517	52.5%
2	88	10.6%	50	7.0%	45	8.0%	160	16.3%	150	15.1%	155	15.9%	79	13.0%	122	12.4%
3	102	12.2%	61	8.5%	55	9.8%	170	17.3%	208	21.0%	160	16.4%	96	15.7%	111	11.3%
4	102	12.2%	80	11.2%	38	6.7%	96	9.8%	150	15.1%	115	11.8%	62	10.2%	80	8.1%
5 (severe disruption)	292	35.1%	264	36.9%	100	17.8%	130	13.2%	241	24.3%	152	15.6%	110	18.0%	155	15.7%
Average	3.12		3.05		2.19		2.33		3.00		2.47		2.47		2.22	
Count	833		716		563		982		991		973		610		985	

Table 3
Ordered probit models of expected disruption scores.

	Commuting to and from work/school/ college		Travelling as part of work		Taking children to and from school		Going to the shops		Visiting friends and family		Hobbies and past-times		Taking children to out-of-school activities or friends		Trips to the doctor or health care provider	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Ran out of fuel	0.371	3.15	0.229	1.82	0.105	0.68	-0.022	-0.20	0.202	1.88	-0.030	-0.27	0.251	1.79	0.005	0.04
Use motorized mode for commuting	0.841	2.20	0.121	0.32	-0.464	-0.87	-0.327	-0.98	0.905	2.66	0.006	0.02	-0.169	-0.40	-0.286	-0.83
Passenger in car for commuting	0.544	1.13	-0.831	-1.50	-0.475	-0.68	-0.842	-1.81	1.287	2.85	0.011	0.02	0.120	0.21	0.161	0.35
Use public transport for commuting	-0.223	-0.53	-0.818	-1.93	-0.853	-1.44	0.011	0.03	1.005	2.69	0.017	0.05	-0.331	-0.68	-0.454	-1.19
Use non-motorized mode for commuting	-1.329	-2.99	-0.877	-2.07	-0.981	-1.66	-0.209	-0.57	0.882	2.37	-0.312	-0.83	-0.455	-0.96	-0.630	-1.66
Gender (dummy for male)	0.140	1.25	0.112	0.91	-0.263	-1.82	-0.116	-1.09	-0.070	-0.67	0.107	1.01	-0.333	-2.53	-0.194	-1.76
Engine size of primary vehicle	1.57x10^{-4}	1.83	2.03x10^{-4}	2.26	2.89x10^{-5}	0.26	-1.99x10^{-5}	-0.24	7.12x10^{-5}	0.90	-3.36x10^{-5}	-0.40	1.74x10^{-4}	1.69	2.81x10^{-5}	0.33
Total number in household	0.026	0.33	-0.097	-1.13	-0.011	-0.10	0.007	0.10	0.023	0.32	-0.035	-0.47	-0.056	-0.57	-0.057	-0.72
Number of children under 16 in household	0.059	0.62	0.109	1.07	0.245	1.93	0.072	0.81	-0.138	-1.60	-0.014	-0.15	0.276	2.44	0.115	1.24
Age	-0.009	-2.16	-0.012	-2.43	-0.003	-0.41	0.005	1.33	-0.001	-0.27	-0.004	-1.09	0.010	1.65	-0.002	-0.52
Total number of motorized vehicles owned	-0.003	-0.03	0.010	0.11	0.052	0.42	0.118	1.39	0.098	1.18	0.120	1.41	0.214	2.01	0.173	1.97
Total vehicle miles of travel	2.21x10^{-6}	0.65	4.68x10^{-6}	1.26	1.63x10^{-6}	0.33	1.17x10^{-6}	0.36	-2.55x10^{-6}	-0.82	4.37x10^{-6}	1.35	-1.83x10^{-6}	-0.41	2.04x10^{-6}	0.61
Income (based on categories)	-3.70x10^{-6}	-1.21	8.85x10^{-6}	2.72	4.16x10^{-7}	0.10	1.32x10^{-6}	0.47	-7.64x10^{-6}	-2.74	-9.98x10^{-6}	-3.47	-1.32x10^{-6}	-0.36	-7.41x10^{-6}	-2.43
Dummy for Social Class A/B	0.204	0.99	-0.127	-0.57	-0.246	-0.93	0.419	2.06	0.312	1.61	0.159	0.79	0.136	0.56	-0.010	-0.05
Dummy for Social Class C1/C2	-0.027	-0.14	-0.223	-1.08	-0.183	-0.77	0.253	1.35	0.141	0.80	0.070	0.38	0.177	0.81	-0.066	-0.36
Dummy for South East	0.012	0.09	-0.185	-1.26	-0.413	-2.19	0.002	0.02	0.133	1.07	0.094	0.73	-0.233	-1.45	-0.037	-0.28
Dummy for Inner London	-0.025	-0.13	-0.086	-0.43	0.330	1.43	0.113	0.65	0.277	1.61	0.150	0.84	0.062	0.28	-0.112	-0.59
Dummy for Outer London	-0.107	-0.60	-0.130	-0.66	-0.032	-0.14	-0.274	-1.57	0.052	0.32	0.207	1.22	0.123	0.57	-0.054	-0.30
?$_1$	-0.066		-0.570		-0.330		0.210		0.198		-0.525		0.656		-0.487	
?$_2$	0.339		-0.368		-0.086		0.679		0.726		-0.087		1.018		-0.081	
?$_3$	0.734		-0.121		0.258		1.260		1.271		0.317		1.458		0.279	
?$_4$	1.099		0.218		0.510		1.715		1.725		0.834		1.806		0.608	
N	499		434		311		499		504		494		335		501	
Log-likelihood	-656.00		-554.06		-362.92		-719.60		-790.30		-742.77		-475.45		-664.84	
Log-likelihood (0)	-736.87		-596.93		-383.61		-734.81		-804.34		-754.63		-496.28		-679.36	
Model significance (chi^2)	0.0000		0.0000		0.0013		0.0335		0.0608		0.1644		0.0012		0.0479	

Table 4
Probability scores generated from ordered probit models

	Commuting to and from work/school/ college		Travelling as part of work		Taking children to and from school		Going to the shops		Visiting friends and family		Hobbies and past-times		Taking children to out-of-school activities or friends		Trips to the doctor or health care provider	
Probability Score Value	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**	**= 4 or 5**	**= 1 or 2**
Reference Probability	0.1997	0.6728	0.5640	0.3418	0.4903	0.3745	0.2152	0.5822	0.0766	0.8116	0.2385	0.6205	0.3474	0.4812	0.3776	0.4811
Ran out of fuel	0.3188	0.5303	0.6519	0.2621	0.5321	0.3355	0.2088	0.5908	0.1100	0.7524	0.2294	0.6318	0.4439	0.3827	0.3794	0.4792
Use motorized mode for commuting	0.4994	0.3470	0.6112	0.2985	0.3126	0.5574	0.1323	0.7035	0.3003	0.4916	0.2404	0.6182	0.2872	0.5486	0.2751	0.5942
Passenger in car for commuting	0.3827	0.4616	0.2516	0.6639	0.3086	0.5618	0.0515	0.8530	0.4437	0.3435	0.2420	0.6162	0.3925	0.4338	0.4399	0.4176
Use public transport for commuting	0.1434	0.7487	0.2558	0.6591	0.1901	0.7030	0.2184	0.5780	0.3360	0.4518	0.2440	0.6138	0.2347	0.6117	0.2219	0.6579
Use non-motorized mode for commuting	0.0149	0.9622	0.2370	0.6806	0.1573	0.7458	0.1591	0.6617	0.2924	0.5007	0.1532	0.7318	0.1983	0.6584	0.1730	0.7201
Gender (dummy for male)	0.2413	0.6206	0.6075	0.3018	0.3870	0.4773	0.1828	0.6270	0.0670	0.8299	0.2730	0.5791	0.2341	0.6125	0.3064	0.5584
Engine size of primary vehicle	0.1785	0.7006	0.5237	0.3798	0.4845	0.3800	0.2181	0.5783	0.0716	0.8211	0.2438	0.6140	0.3159	0.5158	0.3723	0.4867
Total number in household	0.2070	0.6635	0.5258	0.3779	0.4859	0.3787	0.2174	0.5793	0.0799	0.8054	0.2280	0.6336	0.3270	0.5034	0.3563	0.5037
Number of children under 16 in household	0.2166	0.6513	0.6067	0.3026	0.5874	0.2860	0.2367	0.5541	0.0587	0.8465	0.2344	0.6256	0.4537	0.3733	0.4221	0.4354
Age	0.2410	0.6210	0.6311	0.2805	0.5071	0.3587	0.1919	0.6141	0.0789	0.8073	0.2595	0.5951	0.2922	0.5427	0.3907	0.4674
Total number of motorized vehicles owned	0.1989	0.6739	0.5681	0.3379	0.5110	0.3550	0.2514	0.5355	0.0918	0.7839	0.2773	0.5740	0.4293	0.3968	0.4447	0.4129
Total vehicle miles of travel	0.2044	0.6668	0.5778	0.3290	0.4952	0.3699	0.2178	0.5788	0.0739	0.8167	0.2488	0.6079	0.3423	0.4867	0.3834	0.4750
Income (based on categories)	0.1871	0.6893	0.6071	0.3022	0.4924	0.3726	0.2200	0.5758	0.0637	0.8363	0.2016	0.6669	0.3413	0.4878	0.3429	0.5180
Dummy for Social Class A/B	0.2614	0.5964	0.5135	0.3897	0.3935	0.4705	0.3557	0.4164	0.1320	0.7164	0.2905	0.5586	0.3989	0.4272	0.3736	0.4853
Dummy for Social Class C1/C2	0.1924	0.6823	0.4753	0.4269	0.4180	0.4454	0.2960	0.4820	0.0989	0.7713	0.2608	0.5935	0.4147	0.4113	0.3528	0.5074
Dummy for South East	0.2031	0.6685	0.4905	0.4119	0.3309	0.5372	0.2158	0.5814	0.0976	0.7736	0.2686	0.5842	0.2658	0.5738	0.3637	0.4958
Dummy for Inner London	0.1927	0.6819	0.5298	0.3740	0.6201	0.2578	0.2498	0.5375	0.1248	0.7280	0.2875	0.5621	0.3704	0.4567	0.3359	0.5257
Dummy for Outer London	0.1712	0.7104	0.5122	0.3908	0.4775	0.3868	0.1439	0.6850	0.0844	0.7972	0.3072	0.5396	0.3937	0.4325	0.3573	0.5025

Table 5
Attributes of reference individual for calculation of probability scores

Independent variable	**Reference value**	**Value used for calculating change in probability**
Ran out of fuel	Yes	No
Commuting mode	Works at home	Dummy equal to 1 for other modes
Gender	Female	Male
Engine size of primary vehicle	1650 cc	1150 cc
Total number in household	2	3
Number of children under 16 in household	1	2
Age	45	30
Total number of motorized vehicles owned	1	2
Total vehicle miles of travel	16,500	24,000
Income	£25,000	£37,500
Social Class	D	Dummy equal to 1 for other social classes
Region	Northeast	Dummy equal to 1 for other regions