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She's Got a Ticket to Ride: Gender and Public Transit Passes

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SHE'S GOT A TICKET TO RIDE: GENDER AND PUBLIC TRANSIT PASSES

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ABSTRACT

The promotion of public transit is a central policy tool in the German government's efforts to mitigate pollution, congestion, and other automobile-caused externalities. Drawing on a household survey spanning 1997-2007 from Germany, this analysis investigates the decision to purchase a weekly or monthly transit pass against the backdrop of two questions: 1) Does gender play a role in determining the probability that an individual owns a pass? 2) If so, how is this role mitigated or exacerbated by other socioeconomic attributes of the individual and the household in which they reside? These questions are pursued through a combination of descriptive analyses and econometric methods, the latter of which relies on variants of the probit- and heteroskedastic probit model to control for the effects of unobserved heterogeneity that could otherwise induce biased estimates. The model uncovers several determinants of transit pass patronage over which policy makers have direct leverage, including fares, fuel prices, and the siting of transit stops. Moreover, while women are found to have a higher probability of owning a transit pass than men, the model identifies few variables whose impact differs according to gender, with the two exceptions being the number of children in the household and the distance to work. This absence of differential effects implies that policy measures to increase ridership are likely to have a roughly uniform impact among women and men.

Keywords: public transit; household data; heteroskedastic probit

1. INTRODUCTION

In Germany, as elsewhere in the industrialized world, the promotion of public transit is a central policy tool in the mitigation of pollution, congestion, and other automobile-caused externalities. Despite Germany's relative success in capping emissions from transport, which rose by 1% between 1990 and 2005 compared to a 26% increase in the European Union (EEA 2008), public transit use has been on the decline. Between 1994 and 2003, the percent of trips traveled by transit dropped by 1%, contrasted by a 16% increase in motor vehicle trips (DESTATIS 2006). To counter this trend, the country's transport ministry has placed a high priority on improving the competitive position of public transit relative to the automobile (BMVBS 2009).

An important step in this endeavor is to identify the economic and structural factors that draw or repel potential transit customers, thereby enabling the design of measures to increase ridership among those segments of the population where the scope for mode switching is greatest. The impact of gender, in particular, is relevant to such assessments inasmuch as substantial differences between women's and men's mobility behavior has been observed in transit usage (Pickup 1985; Hamilton 2001; Matthies, Kuhn, and Klöckner; 2002). With few exceptions (e.g. Patterson, Haider, and Ewing 2005), women are found to be the predominant transit customers. Nevertheless, the combined effects of entry into the labor force coupled with continued household- and childcare responsibilities have impelled many women to adapt increasingly complex travel patterns (Rosenbloom and Burns 1994; Turner and Niemeier 1997; Sermons and Koppelman 2001). One outcome of these multiple responsibilities is a greater reliance on the car, which in Germany is evidenced by an increase in the share of vehicle kilometers driven by women from 31% in 1996 to 36% in 2007.

While the shifting pattern in the role of women in the household has undoubtedly impacted their propensity to use public transportation, there is to date a dearth of conclusive evidence on how the relationship between socioeconomic circumstance and transit use differs by gender. Although several studies have suggested that women have unequal access to the car and conduct more of their travel by public transportation or by foot (Manning 1978; Guilano 1979; Hanson and Johnston 1985;

Preißner et al. 2000), dissenting evidence has also emerged that points to little difference between men and women in private automobile use (Gordon, Kumar, and Richardson 1989; Rosenbloom 1996). In one of the few studies conducted on this issue in the German context, Heine, Mautz and Rosenbaum (2001) find that children are the most important factor in increasing female car use, which they attribute to the traditional role of women in assuming shopping and accompaniment duties, as well as to security aspects of caring for children in the case of emergencies. A more recent study of German households by Vance and Iovanna (2007) concurs with this view, finding that while women use the car less than men, this difference diminishes with the presence of children and with the availability of a car. The implications of this pattern for transit use, however, have gone largely unexplored.

The present paper aims to fill this void with an econometric analysis that uses an expanded version of the data analyzed by Vance and Iovanna (2007). Specifically, the paper explores transit use from an angle that has heretofore received scant attention in the literature: the ownership of weekly or monthly public transit passes. Understanding the determinants of transit pass ownership is significant to a range of themes that are of importance to transport planning, including efforts to anticipate ridership levels and improve capacity utilization. With regard to the latter, the German data suggests that pass ownership is a good indicator of transit patronage: Those with passes undertake an average of 6.84 transit trips per week, compared with an average of 0.55 for those not owning a pass. Public transit systems across Germany thus have a keen interest in increasing their sale, typically offering steep discounts for monthly passes that average 60% of the standard fare for adults and 75% for high school and university students (Buehler, Pucher, and Kunert 2009).

Following a presentation of the data and some descriptive statistics, the paper proceeds by estimating a probit model of the determinants of transit pass ownership. The specification includes a rich array of explanatory variables, many of which, such as fares and fuel prices, have immediate relevance for policy but have rarely been parameterized using individual level data. This focus on individual choices confers the opportunity to test for heterogeneous responses that is otherwise precluded by the reliance on aggregate data commonly found in the literature. To facilitate interpretation, the assessment moves beyond the standard focus on the significance and magnitude

of the parameter estimates to consider their implications for predicted outcomes. For this purpose, Monte Carlo simulation is employed to explore the predictions of the model and the associated degree of uncertainty. The paper concludes with a discussion of policy implications and suggestions for future research.

2. DATA

The main data source used in this research is drawn from the German Mobility Panel (MOP), a multiyear travel survey financed by the German Federal Ministry of Transport, Building and Housing (MOP 2009). The panel is organized in waves, each comprising a group of households whose members are surveyed for a period of one week over each of three years. The data used in this paper is from 12 waves of the panel, spanning 1996 to 2007, and is limited to individuals over 17 years of age. Of these, 3,711 participate in all three years of the survey, 2,132 participate in two years, and 3,100 participate in once year, yielding a total of 18,479 observations on which the model is estimated. To correct for the non-independence of repeat observations over multiple time points in the data, the regression disturbance terms are clustered at the level of the individual, and the presented measures of statistical significance are robust to this survey design feature.

Individuals that participate in the survey are requested to fill out a questionnaire eliciting general household information and person-related characteristics, including zip code of residence, gender, age, employment status and relevant aspects of everyday travel behavior. In addition to this general survey, the MOP includes a separate survey focusing specifically on vehicle travel among a 50% sub-sample of randomly selected car-owning households. These households are drawn from the larger MOP-data set used in the present analysis. This so-called “tank survey” takes place over a roughly six-week period, during which time respondents record sundry automobile-related information, including the price paid for fuel. As this variable is a potentially important determinant of transit pass ownership, it was linked with the larger sample of households in the MOP by using a Geographic Information System to create a coverage of spatially interpolated fuel prices (in real terms) for all of Germany. The

coverage was then overlaid onto the map of household locations in the MOP data, thereby allowing for each household to be ascribed the locally prevailing fuel price. This process was repeated for each year of the data, yielding a dataset of fuel prices that varies over space and time. An accuracy assessment of the data was undertaken by calculating the yearly average fuel prices and comparing these with those published for the German market by the oil company Aral (Aral 2009). The correspondence between the two sources is tight, deviating by an average of less than 1% over the 1996-2007 time-interval (Fronzel and Vance 2010).

In addition to fuel prices, another important cost-determinant of transit use is the fare. Data on this variable was obtained by an internet-based survey that retrieved the price for a monthly ticket for each of the 90 regional transit authorities (Verkehrsverbünde) in Germany. Each household was then assigned the monthly fare of the Verkehrsverbund in which it is situated. Fares were converted into real terms using a consumer price index for Germany.

The dependent variable used in the model is drawn directly from the MOP and assumes a value of 1 if the individual owns a weekly or monthly transit pass and zero otherwise. Table I presents descriptive statistics that provide some insight into the incidence of this ownership by gender. Consistent with expectations, women are the primary customers of passes, comprising 58.3% of the 15.7% of the sample who owns a pass. Moreover, as seen in the right panel of the table, this predominance generally holds after partitioning the sample according to other socioeconomic attributes. A particularly wide and statistically significant discrepancy is seen among city residents, where 26.2 % of all women hold a transit pass compared with 21.9% of men. Women are also more likely to own a pass in households in which there is at least one car per licensed driver, providing some contradictory evidence to the notion that that women are “captive riders” who only use public transit because they lack access to a car. Interestingly, the only two categories for which the shares are statistically indiscriminant are among students and individuals with children. While the former category is the largest user group overall, it is also the one in which other dimensions of gender roles are likely to be relatively equalized. The presence of children, by

contrast, presumably leads to a more pronounced difference in gender roles, but one that draws women away from reliance on transit.

TABLE I: Incidence of transit pass ownership (%)

	Total share owing a pass	Share of whom are women	Total share by sex		
			Women	Men	Difference in means, Pearson chi ²
Entire sample	15.7	58.3	17.4	13.9	42.18**
City residence	24.2	57.7	26.2	21.9	19.28**
Employed	13.2	53.8	14.8	11.7	20.48**
Licensed driver	12.8	54	13.9	11.7	18.76**
Car available	9.7	57.3	10.6	8.6	12.31**
Student	38.3	55.1	40.1	36.3	2.27
Children present	10.4	53.4	10.4	10.4	0.001

**significant at the 1% level

3. EMPIRICAL METHOD

3.1 The estimator

To explore the pattern presented in Table I more rigorously, the empirical methodology proceeds by specifying a structural model describing the probability of transit pass ownership:

$$y_i^* = \beta'x_i + \varepsilon_i \quad (1)$$

where x is a vector of explanatory variables, ε is an error term, β is a vector of estimated coefficients, and the subscript i denotes the observation. The variable y_i^* measures the utility associated with possessing a transit pass, and is therefore unobservable. We do, however, observe the associated outcome, which can be denoted by the dichotomous variable y_i :

$$y_i = 1 \text{ if } y_i^* > 0 \text{ and } 0 \text{ otherwise} \quad (2)$$

In the present analysis, y_i equals one for individuals who own a pass and zero for non-owners. Referring to equation (1), if the error term is assumed to have a normal distribution, then the parameters β can be estimated using the maximum likelihood method with the probit link function:

$$P(y_i = 1) = \Phi(\beta'x) \quad (3)$$

where Φ is the standard normal distribution function.

One of the key assumptions underlying the probit model is homoskedasticity of the disturbances, the violation of which results in spurious inferences regarding statistical significance and – contrasting with linear regression – inconsistent parameter estimates (Yatchew and Griliches 1984). To address this issue, the present analysis draws on a more general class of models collectively referred to as heterogeneous choice models. These methods can be employed in the context of binary or ordinal models to model the variance of individual level choices and thereby correct for biases induced by heterogeneity. The probit variant of the heterogeneous choice model is:

$$P(y_i = 1) = \Phi\left(\frac{(\beta' x)}{\exp(\gamma' z)}\right) \quad (4)$$

where the numerator is referred to as the choice equation while the denominator is the variance equation. This latter equation contains a vector of variables, \mathbf{z} , that are posited to determine the error variances. For example, women may exhibit greater unobserved variance in their choices than men, which would dictate the inclusion of a gender dummy among the \mathbf{z} . In this regard, one of the main challenges in employing such a model is in correctly identifying the cause of the heteroskedasticity, as theoretical considerations generally provide little guidance. Following Williams (2009a), a stepwise procedure, elaborated below, is consequently employed to specify the variables in the variance equation.

3.2 Interpretation

In interpreting the estimates from the probit model, interest generally focuses on the effects of changes in one of the independent variables on the probability of a zero or one outcome. For the standard probit, this marginal effect is given by:

$$\frac{\partial P(y_i = 1)}{\partial x_k} = \phi(\beta' x) x_k \quad (5)$$

where ϕ is the standard normal density function. The corresponding formula for the heteroskedastic probit accommodates the possibility that the explanatory variable of interest appears in one or both of the choice- and variance equations:

$$\frac{\partial P(y_i = 1)}{\partial w_k} = \phi\left[\frac{\beta' x}{\exp(\gamma' z)}\right] \frac{\beta_k - (\beta' x)\gamma_k}{\exp(\gamma' z)} \quad (6)$$

where the second term drops out if w is only included in the choice equation, while the first term drops out if it is only included in the variance equation.

The marginal effects are generally calculated at the mean of the other independent variables and can be requested in the output of most statistical software packages, though some care must be taken in their interpretation when interaction terms are involved. As Ai and Norton (2003) discuss, the interaction effect for two variables in

non-linear models such as the probit requires computing the cross derivative $\frac{\partial^2 \Phi(\beta'x_i)}{\partial x_{i1} \partial x_{i2}}$, whereas standard computer software typically displays the effect equal to $\frac{\partial \Phi(\beta'x_i)}{\partial (x_{i1} x_{i2})}$.

They show that this latter calculation often results in false inferences with respect to both the sign and significance of the interaction term. Consequently, we follow their recommendation to calculate the interaction effect as given by the cross-derivative.

To further facilitate interpretation, the predicted outcomes and associated 99% confidence intervals for particular variables of interest are plotted using statistical simulation (King, Tomz and Wittenberg 2000). Recognizing that the parameter estimates from a maximum likelihood model are asymptotically normal, the method employs a sampling procedure akin to Monte Carlo simulation in which a large number of values – say 1000 – of each estimated parameter is drawn from a multivariate normal distribution. Taking the vector of coefficient estimates from the model as the mean of the distribution and the variance-covariance matrix as the variance, the simulated parameter estimates can be used to generate expected values and, more importantly, the associated degree of uncertainty. As illustrated below, the generation of confidence intervals, in particular, reveals insights that would otherwise be neglected were the analyst to focus exclusively on the parameter estimates and their standard errors. Annotated code for generating these and all other results presented in the paper, which was written using the Stata software, is available from the authors upon request.

3.3 Explanatory variables

The suite of variables selected for inclusion measures the individual and household-level attributes that are hypothesized to influence the allocation of travel expenditures in maximizing utility. Variable definitions and descriptive statistics are presented in Table II.

TABLE II: Variable definitions and descriptive statistics

Variable	Definition	Mean	SD
Female	1 if female	0.528	0.499
Age	Age of respondent in years	49.326	15.922
Student	1 if respondent is a student	0.081	0.273
Degree	1 if respondent holds a college preparatory degree	0.345	0.475
Licensed driver	1 if respondent holds a driver's license	0.864	0.342
Employed	1 if respondent is employed	0.524	0.499
Distance	Distance to work or school (in 10s kilometers)	0.876	1.865
Car availability	1 if there is at least 1 car per licensed driver in household	0.542	0.498
# adults (>17)	Number of adults older than 17 in household	0.958	0.781
# kids (<18)	Number of kids less than 18 in household	0.469	0.832
Income	Monthly household income in Euros	2349.989	817.709
Fare/fuel price	Monthly fare price divided by the per liter price of fuel	37.786	10.016
Minutes	Minutes required to reach the nearest transit stop by foot	5.695	4.874
Rail transit	1 if the nearest transit stop is serviced by rail	0.125	0.330
Big city	1 if the household is located in a big city	0.414	0.493
Pop. density	Population density in 1000s per square kilometer	0.883	1.050

As many of these variables could either positively or negatively affect the probability of owning a transit pass, it is not always possible to state a priori which effects are expected to prevail. Negative signs are ascribed to the variables that either increase the opportunity- and/or transaction costs of transit use or decrease these costs for automobile use, including household income, the distance to the nearest transit stop, the fare ticket price relative to the fuel price, and dummies indicating driver-license holders and households in which the number of cars equals or exceeds the number of licensed drivers. Positive signs are ascribed to variables that are indicative of the availability or quality of public transit, including population density and the dummies for residence in a large city and for rail transit service at the nearest transit stop. The student dummy is also expected to have a positive sign, as students are typically offered discounts on the purchase of transit passes. The inclusion of time dummies in the model was also explored, but as these were individually and jointly insignificant, they were excluded from the final specification.

4. RESULTS

Table III catalogues coefficient estimates and corresponding marginal effects from the probit models of transit pass ownership. The models are developed sequentially, starting with a standard probit, then adding controls for unobserved heterogeneity that could otherwise produce biases in the estimated coefficients, and finally by including interaction terms to test for differential effects of the explanatory variables by gender.

Turning first to the standard variant of the model in the left panel of the table, most of the coefficients on the individual attributes are statistically significant at the 1% level, and there are no unexpected results with respect to the sign. Confirming the findings from the descriptive statistics in Table I, the female dummy variable has a positive coefficient, suggesting that women have a 0.02 higher probability of owning a transit pass than men. The variables age and distance to work or school, which are specified as a quadratic, both have non-linear effects. Increases in age initially decrease but subsequently increase the probability of owning a pass, with the reversal point occurring at roughly an age of 61. By contrast, increases in distance to work increase the likelihood of owning a pass but at a decreasing rate. As expected, students are more likely to own a pass, as are those with a college preparatory degree, while licensed drivers are less likely.

With the exception of income and the rail transit dummy, the household level variables are also highly significant and have the expected signs. A particularly large effect is seen for the dummy indicating car availability, which decreases the probability by 0.12 relative to individuals in households in which the number of cars is less than the number of license holders. Increases in the fare relative to the fuel price also decrease the likelihood of owning a pass, as does an increase in the distance to the nearest metro stop, while population density and residence in a large city both increase the probability. The two demographic variables, the number of adults and the number of children, each decrease the probability of transit pass ownership by roughly 0.03.

TABLE III: Probit analysis of the determinants of transit pass ownership (n = 18,479)

Standard probit	Heteroskedastic probit	Heteroskedastic probit with interactions
-----------------	------------------------	------------------------------------------

	Coefficient	Marg. effect	Coefficient	Marg. effect	Coefficient	Marg. effect
Choice equation						
Female	0.101**	0.019**	0.219**	0.021**	0.218*	0.027**
Age	-0.057**	-0.002**	-0.117**	-0.001**	-0.114**	-0.001**
Age squared	0.000**	0.000**	0.001**	0.000**	0.001**	0.000**
Student	0.495**	0.116**	0.751**	0.086**	0.731**	0.084**
Degree	0.210**	0.041**	0.403**	0.040**	0.394**	0.039**
Licensed driver	-0.741**	-0.185**	-1.063**	-0.175**	-1.029**	-0.174**
Employed	-0.032	-0.006	-0.247**	-0.023**	-0.280**	-0.027**
Distance	0.127**	0.023**	0.437**	0.049**	0.3554**	0.050**
Distance squared	-0.002**	-0.0004**	-0.037**	-0.004**	-0.033**	-0.003**
Distance*female					1.197*	0.113**
Car availability	-0.618**	-0.119**	-1.712**	-0.117**	-1.744**	-0.116**
# adults (>17)	-0.177**	-0.033**	-0.544**	-0.028**	-0.549**	-0.028**
# kids (<18)	-0.173**	-0.032**	-0.275**	-0.026**	-0.133*	-0.025*
# kids*female					-0.254**	-0.024**
Income	-0.039	-0.007	-0.060	-0.006	-0.054	-0.005
Fare/fuel price	-0.007**	-0.001**	-0.018**	-0.001*	-0.018**	-0.001
Minutes	-0.016**	-0.003**	-0.026**	-0.002**	-0.026**	-0.002**
Rail transit	0.075	0.014	0.124	0.012	0.123	0.012
Big city	0.224**	0.043**	0.311**	0.030**	0.306**	0.030**
Population density	0.283**	0.053**	0.479**	0.066**	0.472**	0.066**
Constant	1.381**		3.396**		3.348	
Variance equation						
Age			0.006**		0.005**	
Licensed driver			-0.219**		-0.229**	
Distance			0.006**		0.006**	
Car availability			0.261**		0.285**	
# adults (>17)			0.104*		0.105*	
Fare/fuel price			0.005*		0.005*	
Population density			0.093**		0.095**	
Fit						
Log-likelihood	-6206		-6123		-6111	
Wald test			97.59**		95.22**	

**significant at the 1% level; * significant at the 5% level

To explore the robustness of these results, the middle panel of Table III presents estimates from the heteroskedastic probit model, which controls for differences in the unobserved variance. Drawing from the full set of predictors in the choice equation, those in the variance equation were selected using a stepwise procedure that excluded variables whose significance levels were greater than 5% (Williams 2009a,b). This resulted in the selection of six variables – age, distance to work, the number of adults, the fare relative to fuel price, population density, and the dummies indicating licensed drivers and car availability. Of these, only the latter has a negative coefficient, suggesting that individuals in households with at least one car per licensed driver have

less variability in the propensity to own a transit pass. Increases in the remaining variables in the variance equation increase this residual variability.

While the addition of the heteroskedasticity parameters significantly improves the fit of the model (166 chi-square with 6 degrees of freedom), the conclusions emerging with respect to the explanatory variables remain largely unchanged. Across the board, the magnitude of the coefficient estimates from the heteroskedastic probit is larger, in many cases over two-fold those of the standard probit model. However, a comparison of the marginal effects calculated from the two models suggests negligible differences for most variables. The one exception is the employed dummy, which is insignificant in the probit model but negative and highly significant in the heteroskedastic probit.

The final step in developing the model involved the inclusion of interaction terms to test for whether the impact of the explanatory variables varied by gender. Several specifications were explored using alternative sets of interaction terms modeled either individually or jointly, none of which had a substantial bearing on the remaining coefficient estimates. Ultimately, two variables were found to have differential impacts by gender, the distance to work and the number of children, both of which have a higher magnitude among females. These differences are indicated in the right panel of Table III, where the positive effect of distance to work on the probability of owning a transit pass is seen to be stronger for women, as is the negative impact of children. By taking the derivative of equation (4) with respect to distance and accounting for the interactions, it is possible to quantify the size of the effects for each gender evaluated at the means of the other explanatory variables:

$$\frac{\partial P(y_i = 1)}{\partial dist} \Big|_{female=1} = \phi \left[\frac{(\beta_1 \overline{dist} + \beta_2 \overline{dist}^2 + \beta_3 + \beta_4 \overline{dist} + \mathbf{x}\boldsymbol{\beta})}{\exp(\gamma_1 \overline{dist} + \mathbf{z}\boldsymbol{\gamma})} \right]_*$$

$$\left[\frac{(\beta_1 + 2\beta_2 \overline{dist} + \beta_4) - \gamma_1(\beta_1 \overline{dist} + \beta_2 \overline{dist}^2 + \beta_3 + \beta_4 \overline{dist} + \mathbf{x}\boldsymbol{\beta})}{\exp(\gamma_1 \overline{dist} + \mathbf{z}\boldsymbol{\gamma})} \right] = 0.056 \quad (7a)$$

and

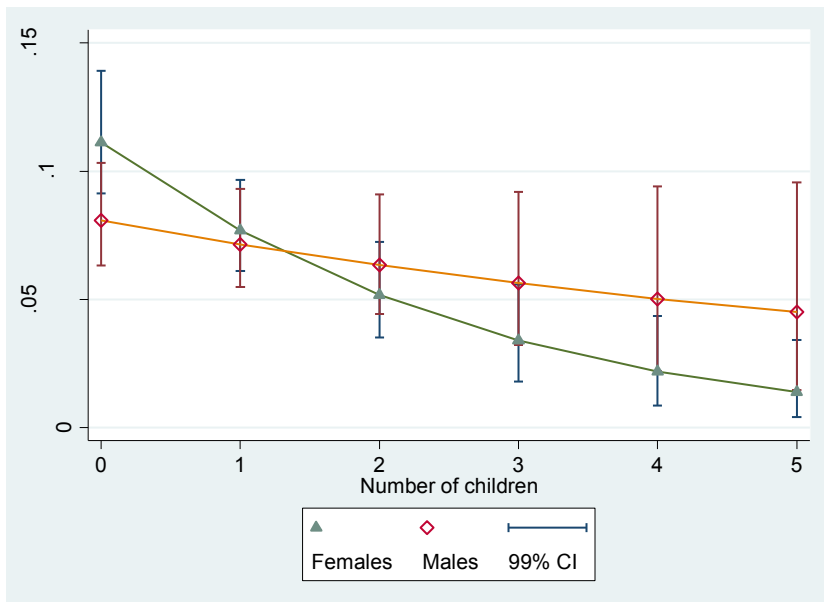
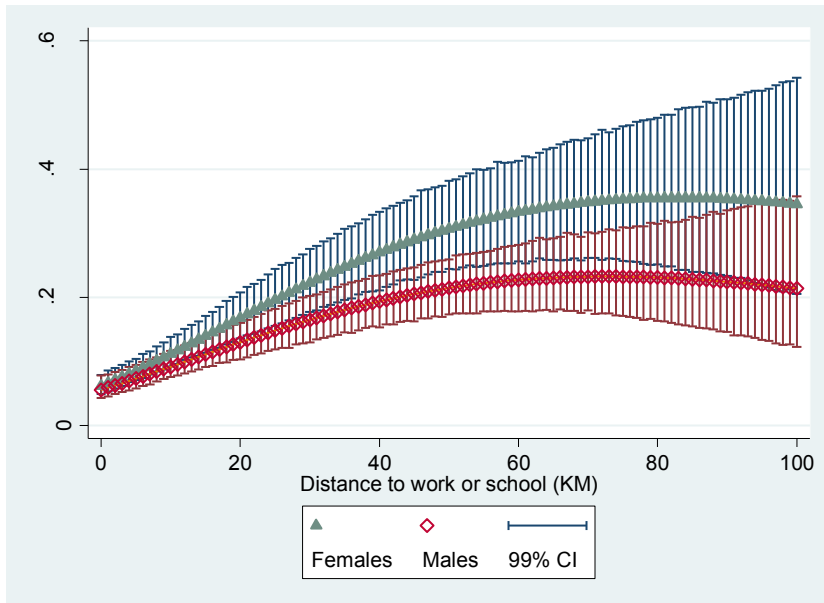
$$\frac{\partial P(y_i = 1)}{\partial dist} \Big|_{female=0} = \phi \left[\frac{(\beta_1 \overline{dist} + \beta_2 \overline{dist}^2 + \mathbf{x}\boldsymbol{\beta})}{\exp(\gamma_1 \overline{dist} + \mathbf{z}\boldsymbol{\gamma})} \right] *$$

$$\left[\frac{(\beta_1 + 2\beta_2 \overline{dist}) - \gamma_1(\beta_1 \overline{dist} + \beta_2 \overline{dist}^2 + \mathbf{x}\boldsymbol{\beta})}{\exp(\gamma_1 \overline{dist} + \mathbf{z}\boldsymbol{\gamma})} \right] = 0.040 \quad (7b)$$

where β_1 , β_2 , β_3 , and β_4 are the coefficients on distance, distance squared, female, and the interaction of distance and female, respectively. Among women, a 10 kilometer increase in the distance to work increases the probability of owning a transit pass by an average of 0.056, while the corresponding effect for men is 0.040. Applying the same formula, we find that additional children decrease the probability for women by 0.039, with a considerably weaker negative effect for men of 0.012.

Further insight into these differences can be gleaned from Figure I, which shows the simulated probabilities of transit pass ownership and confidence intervals using Monte Carlo simulation (King, Tomz and Wittenberg 2000).

FIGURE I: Simulated probabilities of transit pass ownership by distance to work and the number of children



The simulations are generated over a range of values for the variables distance and the number of children while holding the other variables in the model fixed at their mean values. Turning first to the upper panel of Figure I, the impact of distance to work is seen to have a non-linear effect for both sexes, peaking at about 65 kilometers after which it flattens out. Although the expected probabilities for women are higher over the whole range of the data, no statistically significant difference can be discerned between the sexes, as indicated by the overlap of the 99% confidence intervals. In the lower panel of the figure, women with no children are seen to have a higher expected probability of owning a pass than their male counterparts, with a reversal thereafter.

Statistically significant differences in the expected probabilities between the two sexes, however, are again indiscernible over the entire range.

5. DISCUSSION AND CONCLUSION

Drawing on a household survey spanning 1997-2007 from Germany, this analysis has investigated the determinants of transit pass ownership against the backdrop of two questions: 1) Does gender play a role in determining the probability that an individual owns a pass? 2) If so, how is this role mitigated or exacerbated by other socioeconomic attributes of the individual and the household in which they reside? These questions were pursued through a combination of descriptive analyses and econometric methods, the latter of which relied on variants of the probit- and heteroskedastic probit model to control for the effects of unobserved heterogeneity.

The descriptive statistics presented at the outset of the analysis suggests that women are more likely to own transit passes than men, a finding that is confirmed by econometric modeling that holds fixed the influence of other confounding factors related to the individual and their socioeconomic environment. Specifically, the coefficient estimate obtained from the heteroskedastic probit model indicates that women have a 0.027 higher probability of owning a transit pass, which validates other work pointing to women as the primary transit users. At the same time, the modeling uncovers few variables whose impact differs according to gender, with the two exceptions being the number of children and distance to work. This absence of differential effects of the explanatory variables by gender implies that many of the levers available to policy-makers for influencing transit pass patronage, such as fare price setting and the siting of transit stops, are likely to have a roughly uniform impact among women and men.

That said, the fact that a clear majority of pass holders are women suggests that gender-considerations figure in to the formulation of policies to encourage and facilitate the use of transit. Policy-makers should be especially cognizant of the possibility that traditional gender roles play a role in determining mobility behavior. Several studies, for example, have found evidence for so-called patriarchal constraints in dictating first-

choice of car use by men (Pickup 1985; Vance, Buchheim, and Brockfeld 2005; Vance and Iovanna 2007). Children and child-bearing responsibilities seem to be of particular relevance as a mediating factor in this respect. Mirroring the results presented here, Vance and Iovanna (2007) find that while women are less likely to use the car than men, car access is equalized with the presence of children in the household. That children are found to reduce the likelihood of transit pass ownership in the present study, particularly for women, suggests that measures facilitating the use of transit by families – perhaps via allowances for guest-riders – offer promise for increasing ridership.

The focus of this research on transit pass ownership admittedly abstracts from actual transit use, but is nevertheless argued to be indicative of regular patronage and to have relevance for anticipating ridership levels and capacity planning. Moreover, the results presented here can serve as a platform for additional research that probes deeper into the micro-level determinants of transit use and the potentially mediating role of gender. One such extension would examine trip behavior directly, incorporating elements of activity based analysis by modeling transit trips as a two stage decision. The first stage would model the type of activity undertaken (e.g. work, recreation, maintenance), while the second would model the likelihood of transit use, conditional on that activity. Such an approach would provide a more nuanced understanding of how the division of activities within the household impacts mobility behavior. A second extension would involve augmenting the data set used here to include better coverage of supply-side determinants. While some caution is warranted in ascribing a causative interpretation to variables that measure urban form (Vance and Hedel 2007), the positive effects of residence in a large city and population density suggests that individuals are highly responsive to the settlement patterns in their immediate vicinity. Hence, a goal of future work is to pursue this issue further by using GIS to merge in variables that measure the density and service levels of public transit, including the geographical coverage and trip frequency of the transit network.

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REFERENCES

Ai C, Norton, EC (2003) Interaction terms in logit and probit models. *Economic Letters* 80: 123-129.

Aral. Fuel prices.

<http://www.aral.de/toolserver/retailleurope/histFuelPrice.do?categoryId=4000533&contentId=58642>. Accessed July 30, 2009.

BMVBS (Bundesministerium für Verkehr, Stau und Stadtentwicklung), <http://www.bmvbs.de/Verkehr/-,1491/Oeffentlicher-Personennahverkehr.htm>, Accessed July 28, 2009.

Buehler R, Pucher J, Kunert U (2009) Making Transport Sustainable: Insights from Germany. Paper prepared for the Brookings Institution Metropolitan Policy Program. http://www.brookings.edu/reports/2009/~media/Files/rc/reports/2009/0416_germany_transportation_buehler/0416_germany_transportation_report.pdf, Accessed October 22, 2009.

DESTATIS - Statistisches Bundesamt (2006) *Verkehr in Deutschland 2006*. Wiesbaden, Germany.

EEA - European Environmental Agency (2008) *Climate for a Transport Change. TERM 2007: Indicators Tracking Transport and the Environment in the European Union*. EEA Report, No 1/2008, Copenhagen.

Frondel M, Vance C (2010) Driving for Fun? Comparing the Effect of Fuel Prices on Weekday and Weekend Fuel Consumption. *Energy Economics* 32: 102-109.

Gordon P, Kumar A, Richardson HW (1989) Gender Differences in Metropolitan Travel Behavior. *Regional Studies* 23: 499-510.

Guilano G (1979) Public Transport and the Travel Needs of Women. *Traffic Quarterly* 6: 72-83.

Hamilton K (2001) Gender and Transport in Developed Countries. Paper commissioned by UNED as in put for the Expert Workshop "Gender Perspectives for Earth Summit 2002: Energy, Transport, Information for Decision-Making," Berlin.

Hanson S, Johnston I (1985) Gender Differences in Work-Trip Length: Explanations and Implications. *Urban Geography* 6:193-219.

Heine H, Mautz R, Rosenbaum W (2001) *Mobilität im Alltag. Warum wir nicht vom Auto lassen*. Campus Verlag, Frankfurt/New York.

King G, Tomz M, Wittenberg J (2000) Making the most of statistical analyses: Improving Interpretation and presentation. *American Journal of Political Science* 44: 347-361.

Manning I (1978) *The Journey to Work*. George Allen and Unwin, Sydney.

Matthies E, Kuhn S, Klöckner CA (2002) Travel Mode Choice of Women: The Result of Limitation, Ecological Norm, or Weak Habit? *Environment and Behavior* 34: 163-177.

MOP, The German Mobility Panel, http://mobilitaetspanel.ifv.uni-karlsruhe.de/ENGLISH/MOP_Frameset.htm. Accessed March 21, 2007.

Patterson Z, Haider M, Ewing G (2005) A Gender-based Analysis of Work Trip Mode Choice of Suburban Montreal Commuters Using Stated Preference Data. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1924: 85-93.

Pickup L (1985) Women's gender-role and its influence on travel behavior. *Built Environment*, 10: 61-68.

Preißner CL, Hunecke M, Sander C, Backhaus W (2000) Mobilitätsbedürfnisse und Mobilitätsverhalten in der Alltagsgestaltung von Frauen. In: Hunecke, M (Ed.), Gestaltungsoptionen für eine zukunftsfähige Mobilität – Eine empirische Studie zum Zusammenwirken von Raumstruktur und Lebensstil im Mobilitätsverhalten von Frauen und Männern in vier ausgewählten Kölner Stadtquartieren. Werkstattbericht 27, Gelsenkirchen.

Rosenbloom S, Burns E (1994) Why Working Women Drive Alone: Implications for Travel Reduction Programs. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1459: 39-45.

Rosenbloom S (1996) Trends in Women's Travel Patterns. Proceedings of the Second National Conference of Women's Travel Issues 16-34.

Sermons MW, Koppelman FS (2001) Representing the Differences between Female and Male Commute Behavior in Residential Location Models. *Journal of Transport Geography* 9: 101-110.

Turner T, Niemeier D (1997) Travel to Work and Household Responsibility: New Evidence. *Transportation* 24: 397-419.

Vance C, Buchheim S, Brockfeld E (2005) On the Role of Gender as a Determinant of Car Use: Evidence from Germany. In Research on Women's Issues in Transportation Conference Proceedings 2: 59-67.

Vance C, Hedel R (2007) The Impact of Urban Form on Automobile Travel: Disentangling Causation from Correlation. *Transportation* 34: 575-588.

Vance C, Iovanna R (2007) Gender and the Automobile: An Analysis on Nonwork Service Trips. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2013: 54-61.

Williams R (a) (2009) Using Heterogeneous Choice Models to Compare Logit and Probit Coefficients Across Groups. *Sociological Methods and Research* 37: 531-559.

Williams R (b) OGLM: Stata module to estimate Ordinal Generalized Linear Models. <http://econpapers.repec.org/software/bocbocode/s453402.htm>. Accessed April 1, 2009.

Yatchew A, Griliches Z (1984) Specification error in probit models. *Review of Economics and Statistics* 66: 134-139.