Market Price and Income Elasticities of New Vehicle Demands

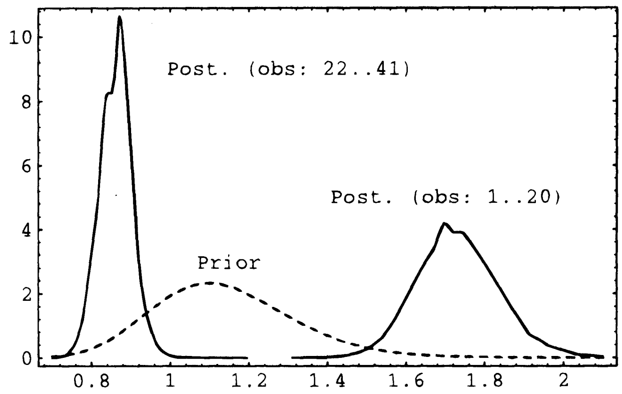
Author(s): Patrick S. McCarthy

Source: *The Review of Economics and Statistics*, Aug., 1996, Vol. 78, No. 3 (Aug., 1996), pp. 543-547

Published by: The MIT Press

Stable URL: https://www.jstor.org/stable/2109802

FIGURE 3.—PRIOR AND POSTERIOR DENSITIES OF THE MRS ($k = (1, 1, 1)$ AND $r^* = 0.95$)




predicted demands and actual demands is determined by the expenditure wasted because of non-optimality. In the context of a Cobb-Douglas illustration, the use of this framework leads to the introduction of a very natural sampling distribution (namely Dirichlet for the budget shares) that automatically respects the nature of the data (budget shares being nonnegative and adding up to one). We then conduct a single-equation analysis using Bayesian methods under a wide range of prior assumptions. Simple importance sampling Monte Carlo proves to be very efficient for the required numerical integration. Results on quantities of economic interest, such as budget shares and efficiencies corresponding to unobserved (future) periods are immediately obtained. The model turns out to be very tractable from a statistical point of view, while possessing quite interesting economic implications.

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# MARKET PRICE AND INCOME ELASTICITIES OF NEW VEHICLE DEMANDS

Patrick S. McCarthy*

*Abstract*—Recent evidence from aggregate models of automobile demand indicates that, when not corrected for quality differences, market price elasticity of demand is substantially biased downwards. This note presents new information on market price and income elasticities derived from a disaggregate demand model that controls for cost, household income, vehicle attributes and perceived quality, consumer search, and manufacturer. Based on an extensive household survey of new vehicle purchasers in 1989, market price and income elasticities are estimated to be −0.87 and 1.70, respectively. Moreover, excluding vehicle quality from a well-specified model is found to have little effect upon the estimated market elasticities.

## Introduction

Over the years, there have been numerous aggregate and disaggregate studies analyzing automobile demands. With some exceptions, the results of these analyses suggest that the demand for new vehicles, by type, is price and income elastic and that the market demand for new vehicles lies in the unitary price elasticity range but is income elastic.[1] Among the aggregate time series demand studies, Nerlove (1957), Suits (1958, 1961), Chow (1960), Dyckman (1966), Hymans (1970), and Juster and Wachtel (1972) have estimated market price elasticities of demand that fall in the (−1.2, −0.6) range with the preponderance of estimates lying below unity. Associated market income elasticities in these studies have generally been greater than 2.0, signifying demand sensitivity to income changes. Hess (1977), on the other hand, finds automobile demands to be price sensitive and income insensitive, estimating these elasticities to be −1.63 and 0.26, respectively.[2] And more recently, Levinsohn (1988), using vehicle type sales data from 1983–1985, estimates the market own price elasticity to be −0.8.

At the disaggregate level, several studies (Lave and Train (1979), Mannering and Mahmassani (1985), Mannering and Winston (1985,

Received for publication April 25, 1994. Revision accepted for publication December 13, 1994.

* Purdue University.

I am grateful to two anonymous referees for their comments on earlier versions of this paper. I would also like to thank J. D. Power and Associates for providing the 1989 data on new vehicle purchases.

[1] Vehicle type price elasticity of demand gives the percentage change in vehicle type demand from a 1% increase in its price, all else constant. The market demand price elasticity is the percentage change in market demand (i.e. the demand for all vehicle types) if the price of all vehicle types increases 1%.

[2] The earlier demand studies generally controlled for price, income, credit availability, and automobile stocks. Hess argued that, by ignoring multiasset interrelationships and multiperiod planning horizons in econometric specifications, the earlier demand studies underestimated price elasticities and overestimated income elasticities. In addition to price of automobiles and income, Hess included the prices of housing and durable goods other than automobiles, the real rate of interest, and measures of expected inflation.

1991), and Tay and McCarthy (1991)) have estimated models of new vehicle demands based upon household level transactions data.[3] Depending upon the study, vehicle price elasticities for particular vehicle types range from $-0.51$ to $-6.13$.[4] Although Lave and Train (1979) did not calculate vehicle type price elasticities, the study did analyze the effect on market shares from a 10% increase in the excise tax on intermediate, large, and luxury vehicles. The resulting market share responses suggest market own price and cross price elasticities equal to $-0.8$ and 1.2, respectively. Mannering and Winston (1985) and Mannering and Mahmassani (1985) also calculated vehicle type income elasticities and, consistent with aggregate demand analyses, found consumer vehicle type demands to be income elastic.[5]

An important question in vehicle demand modeling is the role of vehicle quality, which is absent in all of the aforementioned aggregate models and many disaggregate models.[6] In a recent issue of this *Review*, Trandel (1991), commenting on aggregate models of automobile demand, correctly argued that automobiles are heterogeneous goods distinguished by quality as well as price. If quality is positively correlated with price and demand, then estimating a demand model which excludes measures of quality will produce a downward bias on the price elasticity of demand.[7] To determine the extent of the bias, Trandel estimated double-log regression models on a three year panel of automobile data, from 1983–1985, which included information on 70 automobile make–models. The dependent variable was make–model sales and the independent variables were own price, average price of competitors, own quality, average quality of competitors, two time dummies, and a foreign dummy variable for cars produced outside the United States.[8] In absolute value, quality considerations increased the price coefficient 28% and led to an 83% increase in market price elasticity. In addition, Trandel found, as did Levinsohn, that the physical characteristics of a vehicle were not important determinants of demand once make–model prices entered the model.

The Levinsohn/Trandel model of automobile demand raises an interesting issue. The finding that physical characteristics of automobiles are not significant determinants of demand contrasts with the previously cited disaggregate demand models that find price and physical characteristics to be significant determinants of demand. If, as hypothesized, the lack of significance in the aggregate model is attributed to multicollinearity between price and an automobile's physical attributes, this leads to the troublesome issue of interpreting the coefficients of the included variables, in this case price. High collinearity between price and the physical attributes reduces one's confidence in the estimated price elasticity since the separate effects of the collinear variables cannot be disentangled.

A further question is how serious the specification bias would be in a well specified model. In particular, if vehicle quality were eliminated from a vehicle demand model that initially controlled for price and vehicle characteristics, including quality, would this seriously affect the market price elasticity of demand?

The purpose of this note is to estimate market price and income elasticities based upon a multinomial logit model of new vehicle demands. The underlying data for the analysis is a 1989 nationwide household survey of new vehicle buyers conducted by J. D. Power and Associates. In addition to controlling for socio-economic and vehicle characteristics, the model includes an improved measure of vehicle quality, an index of consumer satisfaction calculated by J. D. Power and Associates for each make and model.[9] The disaggregate demand approach for analyzing market demand sensitivity contrasts with aggregate models of automobile demand because the significantly larger number of observations permit a richer econometric specification, generally involve less collinearity among the explanatory variables, and yield more efficient parameter estimates.

## Econometric Results

Table 1 summarizes the multinomial logit estimation results for new vehicle buyers.[10] The estimated model includes six categories of explanatory variables that reflect vehicle costs, physical characteristics and vehicle style, quality, manufacturer, search activities, and household socio-economic characteristics. In general, the model provides a good fit of the data and the explanatory variables carry their expected signs. Higher vehicle capital costs, as a proportion of household income, and operating costs reduce new vehicle demands. And households living in larger metropolitan areas (with higher congestion costs) exhibit a greater demand for smaller compact vehicles.

[3] Train (1986) summarizes several other studies on automobile demands. The discussion here is limited to analyses based upon new vehicle purchases rather than upon a household's existing vehicle fleet.

[4] Typically, price elasticities are less for smaller sub-compact and compact vehicles relative to larger and more luxurious vehicles. In addition, two-vehicle households are less sensitive to price changes than one-vehicle households.

[5] Mannering and Mahmassani (1985) estimated income elasticities to range from 1.96 for a Chevy Chevette to 7.49 for a Mercedes 280S. Similar to their price elasticity results, Mannering and Winston (1985) also found one vehicle households to be less income sensitive than two vehicle households. In a recent study, Bordley and McDonald (1993) use data on the population income distribution and the average income of a make–model's purchasers to estimate income elasticities. For 1985 make–models, income elasticities ranged from a low of 1.12 for the Pontiac T-1000 to a high of 5.42 for the Jaguar. The income elasticity of demand for the market as a whole was 2.1. The author thanks J. Thursby for providing this reference.

[6] In some disaggregate models, *Consumer Reports* repair frequency or cost index is used to reflect quality. Tay and McCarthy (1991) use a more comprehensive customer satisfaction index, developed by J. D. Power and Associates, based upon a sample of new car buyers.

[7] Many aggregate studies use a first difference formulation in order to reduce the effects of excluded factors, such as quality, which change slowly over time (Dyckman (1966)).

[8] Levinsohn (1988) used data on 100 make–models for the period 1983–1985 to estimate an identical model (except for the inclusion of country-specific dummy variables instead of a single foreign dummy) excluding the quality variables. In his study, Levinsohn developed a methodology for identifying cars that were neighbors or competitors in characteristic space. For each make–model in the analysis, Levinsohn calculated an average price of 'neighboring' cars to reflect the price of a car's competitors. Trandel (1991) refined Levinsohn's results by including quality as well as price in the analysis. Although the nonavailability of automobile quality data for thirty make–models reduced the scope of Trandel's study, this had little effect on his results. When Trandel estimated Levinsohn's original model on the seventy make–models, he obtained results very similar to Levinsohn.

[9] The sample used in this analysis is independent of the sample used for calculating the satisfaction index so that the index is an exogenous measure of perceived quality.

[10] Small and Hsaio (1985) tests for the IIA property led to mixed results. Although the null hypothesis was generally accepted, it tended to be rejected as the number of excluded alternatives increased, despite relatively small differences in the log-likelihoods under the null and alternative hypotheses. This may be due to the relatively large sample used to estimate the model. Small and Hsaio's IIA test is based upon a chi-square test statistic whose degrees of freedom depend upon the number of identifiable parameters from the restricted choice set and not upon sample size. Thus, a model estimated on 1/4 the sample of the existing model will have a chi-square statistic about 1/4 the size of the full sample. Holding all else constant, this could result in not rejecting a null hypothesis in a smaller sample that would be rejected with the larger sample. Confirmation of this was obtained in the present case. Those subsamples that led to IIA rejection with the full sample were reestimated on a 25% randomly drawn subsample. In each case, the null hypothesis that the model is consistent with the IIA property could not be rejected. Li (1978) made a similar point in the context of minimum chi-square logit models.

TABLE 1.—MULTINOMIAL LOGIT MODEL OF NEW VEHICLE DEMAND

| Independent Variables[a] | | Coefficient ($t$-statistic) |
|---|---|---|
| 1. Cost Related Attributes | | |
| Vehicle Price/Annual Income | [1] | −2.452 (−9.1)[j] |
| Operating Cost per Mile (cents)[b] | [1] | −0.4498 (−5.8)[j] |
| Metropolitan Population if ≥ 50000 | [2] | 0.0000173 (1.4)[k] |
| 2. Vehicle Style and Physical Attributes | | |
| Crash Test Dummy Variable[c] | [3] | 0.2409 (3.0)[j] |
| Net Horsepower | [1] | 0.00949 (6.0)[j] |
| Overall Length (inches) | [1] | 0.0166 (5.4)[j] |
| Sport Utility, Van, Pick-up Truck | | 1.445 (4.8)[j] |
| Sports Car Segment[d] | | −1.277 (−4.7)[j] |
| Luxury Segment–Domestic[d] | | −0.4944 (−3.7)[j] |
| 3. Perceived Quality | | |
| Consumer Satisfaction Index[e] | [3] | 0.0085 (3.5)[j] |
| 4. Vehicle Search Costs | | |
| 1st Dealer Visit–Domestic[f] | | 3.034 (11.1)[j] |
| 1st Dealer Visit–European | | 4.274 (15.2)[j] |
| 1st Dealer Visit–Asian | | 3.726 (11.6)[j] |
| Subsequent Dealer Visits–Domestic | | 0.3136 (5.6)[j] |
| Subsequent Dealer Visits–European | | 0.7290 (5.7)[j] |
| Subsequent Dealer Visits–Asian | | 0.3337 (5.9)[j] |
| Re-Purchase Same Brand[g] | [1] | 2.320 (2.0)[i] |
| 5. Socio-economic Related Variables | | |
| Pacific Coast–Domestic | | −1.269 (−5.0)[j] |
| Age ≥ 45–Domestic | | 0.9511 (4.8)[j] |
| 6. Manufacturer Dummy Variable[h] | | |
| Chrysler | | 1.007 (4.7)[j] |
| Ford, General Motors | | 1.721 (8.5)[j] |
| Honda, Nissan, Toyota | | 1.267 (9.1)[j] |
| Mazda | | 1.005 (5.5)[j] |
| log-likelihood at 0–$L(\mathbf{0})$: | | −4235.39 |
| log-likelihood at convergence–$L(\beta)$: | | −3095.89 |
| $-2(L(\mathbf{0})-L(\beta))$: | | 2279.0 |
| $\rho^2$ | | 0.26 |
| No. observations: | | 1564 |

Note: Data for this analysis came from J. D. Power and Associates 1989 New Car Buyer Competitive Dynamics Survey of 33,284 households. This is a quota-based sample which contains information on the new vehicle purchased, household socioeconomic and demographic attributes, and various activities associated with purchasing a vehicle. After eliminating observations with missing information, 28,235 usable records remained. The 1564 households in this analysis is an approximate 5% sample of the usable records. In order to have a random sample of respondents, the 1564 observations were randomly drawn under the constraint that the make-model share in the sample equaled the make–model share in the population.

Supplementing the data in the J. D. Power data set, the 1989 *Automotive News Market Data Book*, *Consumer Reports*, and the *1989 Car Book* provided information on price, warranties, exterior and interior size, fuel economy, reliability, and safety for each of the 191 make-models available in 1989. Gasoline prices were obtained from the offices of the *Oil and Gas Journal* and population data from the Bureau of the Census.

Each observation was assigned a choice set of 14 alternatives randomly drawn from the full set of 191 alternatives. Combined with the observed choice, the resulting set of 15 alternatives is the respondent's estimation choice set. McFadden (1978) has shown that defining choice sets in this way satisfies a uniform conditioning property so that the correction term for the alternative sampling bias is identical for each alternative. This implies that the correction terms cancel out of the choice probabilities and standard multinomial logit algorithms can be used to estimate the model.

[a] Numbers in brackets identify the vehicles to which the variable is associated. The definitions are
[1] all vehicles;
[2] compact vehicles only;
[3] automobiles only.
For variables without numbers, the context is self-explanatory. For example, 1st Dealer Visit–Domestic is associated with domestic vehicles and Chrysler is associated with all Chrysler makes.

[b] Operating Cost per Mile is the ratio of the average gas price prevalent in the respondent's state divided by the vehicle's gas mileage.

[c] Crash Test Dummy equals 1 if, based upon government crash tests, the *1989 Car Book* reported the vehicle as most crashworthy. This variable is defined only for automobiles.

[d] J. D. Power and Associates classify vehicles into one of nine segments. Sports Car Segment equals 1 if the vehicle was classified in this segment, 0 otherwise. Similarly, Luxury equals 1 if the vehicle was classified in the luxury segment and 0 otherwise.

[e] The Consumer Satisfaction Index is alternative specific to automobile make–models since the index was not calculated for vans, pickups, and sport utility vehicles.

[f] Total domestic (European, Asian) dealer visits are the number of different dealerships selling domestic (European, Asian) make-models the respondent visited. One might argue that the dealer visits variables in the model are capturing residual consumer heterogeneity. To explore this, a number of vehicle choice models were estimated with various socio-economic characteristics including education, previous dealer experience, gender, marital status, race, and household position. These variables were not found to be significant determinants of choice. In addition, regression models of total dealer visits which used socio-economic characteristics, vehicle quality, and previous dealer experience as instruments were estimated. The predicted values were then included in the vehicle choice models. Qualitatively, the estimated coefficients were similar to those reported in Table 1 except that the coefficients for dealer visits (Domestic, European, and Asian) and associated $t$-statistics (in the 2.5–3.3 range) were lower. These results suggest that residual consumer heterogeneity is not a serious problem. Overall, however, the model using predicted dealer visits led to a poorer model fit ($\rho^2$ = .13 versus .26 reported above) which reflects the relatively low $R^2$s (.07–.26) in the dealer visits regressions. The results reported in Table 1 include actual dealer visits due to the model's superior fit.

[g] In earlier runs of the model, Re-Purchase Same Brand was a dummy variable which equaled 1 if current make/model purchase was the same as the make/model on the previous purchase occasion. However, since Re-Purchase Same Brand is a lagged dependent variable, its inclusion may bias the parameter estimates. Therefore, Re-Purchase Same Brand reported in Table 1 is predicted brand loyalty based upon a logit model of brand loyalty. Instruments used to estimate brand loyalty included annual income, education, residence, gender, household position, and vehicle make.

[h] Manufacturer reflects nameplate country of origin rather than manufacturing production site. The normalizing alternatives for Manufacturer include European and other Asian.

[i] Significant at the 0.05 level, two-tail test.

[j] Significant at the 0.01 level, two-tail test.

[k] Significant at the 0.10 level, one-tail test.

Consistent with expectations, the disaggregate model is better at disentangling price effects from those associated with physical characteristics and vehicle style. Vehicle safety, net horsepower, and overall length are important determinants of demand. Relative to automobiles and station wagons (the excluded vehicle styles), consumers exhibit a greater demand for vans, sport utilities, and pick-ups, a smaller demand for sports cars, and a smaller demand for domestic cars in the luxury segment, all else constant. Also consistent with expectations, as well as Trandel's results, demand is positively related to increases in perceived quality.

Vehicle search and transactions cost variables are strong determinants of vehicle demands. Dealer Visits entered separately for Domestic, European, and Asian vehicles in order to test for differential search effects. Also, the model includes two separate dealer visit variables, 1st Dealer Visit and Subsequent Dealer Visits, to test for decreasing returns to search.[11]

The positive sign on each of these variables indicates that Dealer Visits has a net positive effect, which implies that information benefits more than offset search costs from an additional visit. The results in table 1 are also consistent with decreasing returns to search. For Domestic, European, and Asian brands, the coefficient estimate for 1st Dealer Visit is significantly larger than the associated coefficient for Subsequent Visits. Further, comparing the magnitudes of the effects, the first visit to a European dealer has the greatest impact on demand whereas the first visit to a domestic dealer has the least effect. Although the ordering does not change for subsequent visits, the marginal effect of additional visits to dealerships that sell domestic vehicles is nearly equal to the effect of subsequent visits to dealerships that sell Asian vehicles.

Re-Purchase Same Brand is also expected to reflect search and transactions costs associated with vehicle buying activities. Since consumers who re-purchase the same brand are expected to incur lower search related costs, re-purchase behavior is expected to increase vehicle demand, all else constant. From table 1, Re-Purchase Same Brand carries its expected sign and is significant at the 0.05 level.[12]

All else constant, younger consumers and consumers residing on the West Coast have smaller demands for domestic vehicles. And relative to other Asian and European (the excluded groups) nameplates, consumers exhibit higher demands for Chrysler, Ford, General Motors, the Japanese "big 3," and Mazda.

Market price and income elasticities, based upon the results in table 1, are reported in table 2, column 2. Own price market elasticity, which assumes a 1% increase in the price of all 191 make–models offered in 1989, is $-0.87$ indicating that new vehicle demands are price inelastic. Table 2 also reports the market cross price elasticity and the income elasticity of demand. A 1% increase in the prices of all but one make-model increases the market demand for the make-model 0.82%. And consistent with other studies, the demand for new vehicles is sensitive to income. A 1% increase in annual household income produces a 1.70% increase in market demand, all else constant.

Column 3 in table 2 also reports the elasticities when Perceived Quality is excluded from the model. In contrast with Trandel's findings, we see that the market elasticities are virtually unchanged.[13] Although vehicle quality is an important determinant of demand, this suggests that excluding vehicle quality from *well specified* demand models will not lead to serious specification biases in market price and income elasticities.

TABLE 2.—AGGREGATE MARKET PRICE AND INCOME ELASTICITIES

| (1) Variable | (2) Market Elasticity (with Perceived Quality) | (3) Market Elasticity (without Perceived Quality) |
|---|---|---|
| Vehicle Own Price | −0.87 | −0.85 |
| Vehicle Cross Price | 0.82 | 0.80 |
| Annual Income | 1.70 | 1.66 |

Note: Author's calculations. For elasticity formulations, see McFadden (1979).

TABLE 3.—AGGREGATE PRICE AND INCOME ELASTICITIES FOR MARKET SEGMENTS

| Market Segment | Elasticity with Respect to Own Vehicle Price[a] | Cross Vehicle Price[a] | Annual Income |
|---|---|---|---|
| Domestic | −0.78 | 0.28 | 1.62 |
| European | −1.09 | 0.76 | 1.93 |
| Asian | −0.81 | 0.61 | 1.65 |

[a] Author's calculations. The own price elasticity assumes a 1% increase in the price of all vehicles in the segment. The cross vehicle price elasticity reflects a 1% increase in the price of all vehicles *not* in the market segment.

In addition to disentangling price and vehicle characteristic effects on vehicle demand, an advantage to disaggregate demand models is the ability to analyze alternative market segments. Table 3 reports price and income elasticities calculated for Domestic, European, and Asian manufacturers in order to investigate whether altered economic circumstances equally affect the demands for domestic and foreign vehicles. This is of interest given the erosion of domestic market share to foreign competition, particularly Asian competitors, over the past twenty years. The demands for Domestic and Asian vehicles are price inelastic but equally sensitive to "own segment" price increases whereas the demand for European vehicles is more sensitive to price. The European segment also exhibits the largest cross price elasticity but here the Asian, relative to the Domestic, segment is twice as sensitive to "out-of-segment" price increases. Last, and similar to the market as a whole, U.S. demand in each segment is income elastic. Consistent with "own segment" price elasticity measures, the demand for European vehicles is most income elastic and consumer demands for Domestic and Asian vehicles are equally sensitive to changes in household income.

## Conclusion

Recent evidence suggests that vehicle demand models that fail to control for vehicle quality lead to potentially serious biases in estimating market price elasticities of demand. With an intent to explore this issue, an extensive set of microdata for 1989 new vehicle buyers was used to estimate a multinomial logit model of new vehicle demands that controlled for cost, vehicle style and physical characteristics, quality, search behavior, and manufacturer. Based upon this model, and consistent with many aggregate demand models, the demand for new

[11] The author is grateful to an anonymous referee for suggesting the disaggregation of dealer visits.

[12] Some analyses (e.g., Mannering and Winston (1991)) interpret this variable as brand loyalty. Although one can't assess whether the variable is capturing loyalty or search related costs, the effect is the same. A brand loyal consumer engages in less searching than a "shopper." In addition to the reported model, a likelihood ratio test was used to examine whether the effect of Re-Purchase Same Brand differed across nameplate country of origin, defined as Domestic, European, and Asian. The null hypothesis that the separately estimated coefficients are equal could not be rejected at any reasonable significance level.

[13] The slight decrease in the elasticities reflects a small estimated negative covariance between price and quality parameters.

vehicles was found to be price inelastic with an estimated market own price elasticity equal to $-0.87$.[14] Market cross price elasticity was estimated as 0.82 and new vehicle demands were found to be income elastic with an estimated elasticity of 1.70. Importantly, the results also indicate that the exclusion of vehicle quality, although found to be an important determinant of vehicle demands, may not lead to significant biases in characterizing market demands if the vehicle demand model is well specified.

Segmentation analysis also revealed similar demand responses in the Domestic and Asian manufacturer segments, respectively, to price and income changes. On the other hand, the demand for Asian vehicles benefited more than that for Domestic vehicles from a 1% price increase in the non-Asian and non-Domestic segments, respectively.

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[14] Notwithstanding that the elasticity measures obtained here are similar to many estimates identified in aggregate time series analyses, this study is silent on the temporal character of the elasticity measures. There has been little research on the temporal stability of cross sectional estimates and the work that is available identifies variability in the estimates. Mannering and Winston's (1991) study of brand loyalty found that, relative to new vehicle purchases in a pre-1980 period, the price elasticity of demand for new vehicles in the post-1980 era was 20% lower.

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# DOES UNION MEMBERSHIP MATTER? THE EFFECT OF ESTABLISHMENT UNION DENSITY ON THE UNION WAGE DIFFERENTIAL

Kevin T. Reilly*

*Abstract*—This paper examines the union's effect on wages using a unique set of variables: dummy variables for the density of unionization in the establishment for which the individual works. The results suggest that after controlling for establishment union density a union member wage gain is only observed for the lowest level, the 1% to 25% density range. For the 26% or greater establishment union density ranges the union's effect on wages is for all individuals working in the establishment and not just union members. The wage gain is 20% for both the establishment union density ranges of 26% to 50% and 51% to 75%. Individuals working for an establishment with a greater than 75% establishment union density achieve a wage gain of 64%.

## I. Introduction

Traditionally, the union effect on the wage is measured by a dummy variable which tests whether the individual is a member of a union or bargaining unit. The contribution of this study to the union wage differential literature is to use a unique set of variables in the wage

Received for publication November 4, 1991. Revision accepted for publication January 9, 1995.

* University of Leeds.

This is a revised version of chapter four of my 1991 unpublished University of Toronto dissertation. The data set used in this paper was collected by R. Apostle, D. Clairmont and L. Osberg of Dalhousie University using funds provided by The Social Science and Humanities Research Council, The Council of Maritime Premiers and Dalhousie University. A special thanks to this group and their funding agencies. Thanks also to seminar participants at McMaster University, University of Waterloo, 1992 Winter Meetings of the Econometric Society in New Orleans and the 1992 meetings of the Canadian Economics Association in Charlottetown. A special commendation to A. Brumwell for help under difficult circumstances. M. Gunderson, P. Kuhn, C. Robinson, L. Bailey and two extremely generous referees provided comments which improved the paper. J. Ham's criticisms led to a substantial improvement in the quality of the paper and for this effort I owe a debt of gratitude. The usual caveat applies.