Information Technology and Transportation: Substitutes or Complements?

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12 January 2014

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Abstract

The increased prevalence of Information and Communications Technology (ICT) provides opportunities to substitute ICT for transportation. However, ICT can also be a complement for transportation, and prior research on the effect of ICT on travel for specific purposes has shown mixed results. Therefore, I examined the relationship between ICT and transportation on a larger scale, using a modified Quadratic Almost Ideal Demand System (QUAIDS) model to calculate expenditure and price elasticities for several categories of ICT and transportation goods. Among other results, I found that cellular service was a complement for private transportation, while home Internet service had no effect.

Keywords: Transportation, Consumer Expenditures, Information Technology *JEL:* D12 O33 R22 R41

1 Introduction

Even the most cursory observation of society reveals the increasing role that Information and Communications Technology (ICT) play in the daily lives of many individuals. Within the last two decades, the Internet has developed to the point that many activities that once required consumers to travel, such as banking or attending business meetings, can now be done online. Additionally, data on ICT

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ownership and use indicates that the use of these products is increasingly prevalent among American consumers. Total computer ownership has increased dramatically in recent years. According to US Consumer Expenditure Survey (CES) data, while only 54% of households owned a computer in 2001, 79% of households owned computers in 2011. The average number of computers owned by households similarly increased over that period, from 0.62 in 2001 to 1.29 in 2010. Similarly, the use of the Internet has increased greatly in recent years. Research from the Pew Internet and American Life Project indicates that, as of 2010, two-thirds of American adults had a home broadband Internet connection (Smith, 2010a). Additionally, 47% of American adults used laptop computers for wireless Internet access in May 2010, an increase of 21% from April 2009 (Smith, 2010b). Forty percent of adults accessed wireless Internet services from their cellular phones in May 2010, up 25% from April 2009. The survey also found that wireless Internet use varies considerably by age, with 84% of those aged 18-29 being wireless Internet users in May 2010, while only 20% of adults over 65 used such devices.

Over this same period, Consumer Price Index (CPI) data indicates that gasoline prices in the United States have increased at a rate far greater than inflation, increasing from an average price of $1.073 per gallon in January 1992 to $3.399 per gallon in January 2012. Because gasoline is used for every form of transportation under consideration, it would be reasonable to assume that this increase would affect demand for transportation. Therefore, given the increasing prevalence of technological alternatives to transportation, it would seem logical for consumers to choose to substitute ICT for transportation.

In addition to potential cost savings for consumers, there are potential macroeconomic benefits if consumers do choose to regularly substitute ICT for transportation. Due to the important role of oil in the economy, oil price fluctuations are known to have large macroeconomic effects. Research on the macroeconomic effects of oil-price shocks indicates that an increase in oil prices decreases GDP, with an oil-price/GDP elasticity of -0.055 (Jones et al., 2004). While far from the only factor, decreases in consumer demand for goods in response to these oil-price increases partially explains the negative effect on GDP. Therefore, if consumers would rely more on ICT and less on gasoline, it might have a positive effect on macroeconomic stability, in addition to partially shielding those individuals from the harmful effects of oil-price fluctuations. A decrease in transportation use would also reduce the negative externalities caused by transportation use. Americans' heavy use of transportation results in numerous negative externalities, such as pollution, traffic congestion, and vehicle accidents. Therefore, if a decrease in the use of transportation can be brought about through substituting ICT, it may have a positive effect on societal welfare.

However, despite these potential societal benefits and the notion of substitution between these two products being intuitively appealing, previous literature has demonstrated that the relationship between these products is quite complex and that information technology may serve as either a substitute or a complement for transportation. Banister and Stead (2004) identify several significant factors that contribute to the complexity of the relationship between ICT and transportation, including the possibility that megatrends such as globalization and the gradual transition to an information-based economy may increase the demand for both ICT and transportation. Other possibilities raised by Banister and Stead include the availability of ICT leading to decentralization, requiring longer trips each time an individual travels, as well as ICT use increasing an individual's social and business contacts, leading to an increased demand to meet with those contacts.

While not directly addressing transportation, Gaspar and Glaeser (1998) and Panayides and Kern (2005) developed theoretical models of the relationship between ICT and the decision to reside in cities. Both models indicated that improvements in ICT could serve to either increase or decrease the demand for face-to-face contact in cities, depending on whether the complementary effect of ICT leading to an increased demand for overall contact outweighed the substitution effect from ICT becoming a more attractive alternative to face-to-face contact. In both models, the complementary effect occurs when those in cities have more total electronic interactions than those in rural areas. Given that location of residence would likely influence both total transportation demand and the type of transportation demanded, the relative strength of the these effects is important for understanding the relationship between ICT and transportation.

Additionally. empirical evidence indicates that the increased availability of resources on the "information superhighway" has done little to decrease congestion on American highways. The 2011 Urban Mobility (Schrank et al., 2012) report indicates that the average American commuter spent 34 hours per year in 2010 commuting due to traffic, just one hour less than the 35 hours spent in traffic in 2000. The cost of the time lost and the fuel wasted across American commuters in 2010 was estimated to be $101 billion dollars annually, compared to $79 billion (in 2010 dollars) in 2000. While there is no reason to assume that the traffic congestion is due to ICT, the rapid increase of ICT prevalence seems not to have done much to decrease it. The trend of increasing consumer expenditures on transportation is also evident in the CES data, with an 8.0% rise in transportation expenditures reported in 2011, which is a larger increase than in any other expenditure category.

On the aggregate level, Choo, Lee, and Mokhtarian (2007) found, in their study of United States aggregated consumer expenditures on ICT and transportation from 1984-2002, that ICT had complementary effects on some forms of transportation spending and substitution effects on others, indicating a complex relationship between communications spending and transportation spending. They found that electronic communications were substitutes for non-personal-vehicle transportation, but complements for private-vehicle purchases and operating expenditures. They also noted that the transportation expenditures were more price- and income-elastic than were the communications expenditures. However, the choice to examine spending on an aggregate level rather than on an individual level left a very small sample size of only nineteen aggregated observations. Given that the income, demographic characteristics, region, and other significant considerations affecting consumption vary among the individuals surveyed, treating the surveyed consumers as one entity would not provide a comprehensive assessment of demand for these products and services. Transportation in particular has been shown to have elasticities that vary significantly based on income (Blundell et al., 1993), so an aggregate measurement would likely yield inaccurate results. Also, because the availability and prevalence of communications technology has increased considerably since 2002, consumer choices regarding ICT and transportation spending may have changed as well.

Prior literature indicates that the nature of the effect may vary based on the purpose of travel. Personal travel is typically characterized as belonging to three general categories: mandatory, which includes work-related travel such as commuting to work, or travel related to education; maintenance, such as shopping, banking, and obtaining healthcare; and discretionary, which is traveling for leisure activities (Andreev et al., 2010). Salomon and Mokhtarian (2008) identified several uses of ICT that have personal-travel-related applications: mobile telephones; telecommuting; teleconferencing; teleshopping; and teleservices, which include distance learning and telemedicine; and teleleisure. The proliferation of mobile telephone use among individuals has enabled consumers to hold one-on-one conversations from a variety of locations. This may have the effect of reducing "deadweight trips," which are trips that do not accomplish their intended purpose, but it may also enable consumers to make trips with less advance planning due to the increased ability to contact all relevant parties "on the go." Telecommuting, which is by far the most frequently studied form of ICT regarding its effects on transportation, has been shown by numerous studies to have a substitution effect on transportation (Andreev et al., 2010). However, the prevalence of telecommuting, and its effect on travel, often vary considerably depending on the type of worker (self-employed, salaried employees, distant workers, etc.) and is, therefore, quite difficult to measure (Salomon and Mokhtarian, 2008). Studies of teleshopping and teleservices, however, have had very different results. Most studies examining the effect that the use of ICT had on travel demonstrated a neutral or complementary effect (Andreev et al., 2010). However, Sinai and Waldfogel (2004) did find that consumers who live further away from stores were more likely to purchase books and clothing online, indicating that those who would have to travel further to shop may substitute teleshopping for transportation.

One area that may have a significant effect on travel, but is often overlooked, is that of teleleisure. Yet given that leisure travel constitutes between one-third and one-half of total travel (Mokhtarian et al., 2006), this type of travel must be carefully considered when examining the effects of ICT on travel. Many modern leisure activities, from socializing to playing games, are now done online. These leisure activities may take the place of travel. Yet ICT may also lead to an increase of leisure travel by enabling consumers to locate travel bargains or by stimulating the desire to meet online friends. A study of time-use among Hong Kong residents found that ICT use led to more use of transportation for leisure purposes, meaning that ICT served as a complement for leisure travel rather than as a substitute (Wang and Law, 2007). This study is consistent with the other research surveyed by Andreev et al. (2010), which found either no relationship or complementarity relationships between ICT and leisure travel.

This study helps fill a gap in the literature by looking at the relationship between multiple forms of technology and transportation on a large scale, using household-level rather than individual-level expenditure data. In their survey of research on the relationship between ICT and transportation demand, Aguilera, Guillot, and Rallet (2012) note that while the complementary effect has been found more often, the relationship between ICT and transportation remains unclear. They note that previous studies often concern themselves with only single technologies and/or single purposes of travel, rather than looking at the overall relationship between ICT and transportation. They also note that previous studies have been limited by examining individual behavior rather than that of the household as a whole.

The purpose of my research is to investigate how consumers' ICT expenditures influence their transportation expenditures. Using household-level data (microdata) from the 2005 - 2011 Consumer Expenditure Surveys (CES) combined with aggregate price index data from the Consumer Price Index (CPI), both produced by the U.S. Bureau of Labor Statistics (BLS), I estimated a model of consumer expenditure shares using a variation of the Quadratic Almost Ideal Demand System (QUAIDS) (Banks et al., 1997) that adjusts for censoring and sample selection bias, which is explained in further detail below. The QUAIDS model is designed to estimate a demand system consistent with both microeconomic theory and the available expenditure and price data, which can then be used to estimate the price and expenditure elasticities of various technology and transportation expenditures. Additionally, I controlled for demographic factors to determine how these factors influence consumer demand.

2 Methods

2.1 Description of Data

The estimation of a demand system using the QUAIDS model requires both consumer expenditure data and price data for each expenditure category. The consumer expenditure data is taken from the US Consumer Expenditure Survey (CES) over the period ranging from February 2005 to March 2012. The CES consists of two separate surveys—the interview survey and the diary survey. Because the interview survey includes all of the expenditures needed for this model, I used data only from the interview survey. The interview microdata consist of approximately 7,000 household-level observations per quarter. Each household is interviewed for five consecutive quarters on a rotating basis; therefore, at least one-fifth of the sample is new each quarter. However, since the first-quarter interview is designed to collect demographic data, only four of those quarters include expenditure data.

It is worth noting that the term household, in the context of this paper, refers to a consumer unit (CU) as defined by the BLS. A consumer unit consists of people who live together and combine their incomes to make joint expenditure decisions, or live together and are related by either blood or marriage. Roommates who live together but do not make joint financial decisions are defined as two separate consumer units, while married couples with separate finances are considered as one consumer unit.

In order to get a better picture of expenditure patterns on infrequently purchased goods such as airplane tickets and computers, I aggregated consumer expenditures across all four quarters for each household in the survey. Therefore, only those households for which all four quarters of expenditure data were available were included in the analysis. There are several reasons why a household may not have completed all four interviews: the household may have had their first interview(s) prior to 2006, the household may have had its last interview(s) after March 2012, or the household may have left the survey due to having moved or due to deciding that they no longer wanted to participate in the

Table 1: Descriptive Statistics by Length of Survey Participation

	In all four quarters	Not in all four quarters	Whole sample
n	32459	38624	71083
Age	51.639	43.967	47.471
	(16.553)	(17.548)	(17.522)
Homeowner	0.738	0.487	0.601
	(0.440)	(0.500)	(0.490)
Married	0.564	0.443	0.498
	(0.496)	(0.497)	(0.500)
Post-HS education	0.650	0.647	0.648
	(0.477)	(0.478)	(0.477)
Has children	0.307	0.315	0.311
	(0.461)	(0.464)	(0.463)
Avg. quarterly expenditure	12225.040	10833.390	11468.910
	(9122.679)	(9537.857)	(9376.143)
City with pop. $>$ 4 mil.	0.343	0.334	0.338
	(0.475)	(0.472)	(0.473)
Rural	0.062	0.047	0.054
	(0.242)	(0.212)	(0.226)
standard deviation in parentheses			

survey. I also removed 29 households that reported total expenditures of less than or equal to zero. Therefore, out of a total of 71,083 households interviewed for one or more quarters, 32,459 were used in this analysis.

However, the subset of households who were interviewed for all four quarters are not a random sample. If a household moves from one house to another during the survey period, the new household is interviewed in place of the previous household. As can be seen in Table 1, 74% of households that participated in all four quarters of the survey were homeowners, compared to only 49% of those who did not. The average age of the respondent and spouse were considerably higher in those households that participated in all four quarters than those who did not, with respective average ages of 51.6 and 44.0. Households who participated in all four quarters also had a higher average quarterly expenditure than those who did not, and differed in some other demographic characteristics. The differences in the means between those who were included and those who were not included were statistically significant for all categories in the table other than post-high-school education. Therefore, I applied a sample selection bias adjustment to the QUAIDS model, which is explained in greater detail below.

Due to the need to have price data that accurately represents CES expenditure categories that cover multiple products, the price data is taken from the Consumer Price Index (CPI). Because the QUAIDS model calculates demand and elasticities based on relative prices rather than absolute prices, using price-index data should not affect the validity of the results. The CPI does not provide product-level data, so I calculate the demand equations and the elasticities based on aggregated price indexes that combine several similar products into a single price index. Because the quarterly spending data is based on the three months prior to the interview and the price index data is monthly, I created an annual price index using the prices for three months before the first interview through the month before the last interview. For example, if a household had their first interview in May 2009, their interviews would cover expenditures made between February 2009 and January 2010, and therefore the average prices that they faced over that period is the average of the indexes for each month during that time period.

To simplify the calculation process and ease the interpretation of results, as well as to enable the matching of CPI price data and CES expenditure data, I aggregated expenditures from several categories into broader expenditure categories based on similar product or service use and combined them with the appropriate aggregate price category. My aggregated technology expenditure categories are computers, home Internet service, and cellular phone plans. My aggregated transportation categories are airfare, other intercity public transportation, private transportation expenditures—which include car payments, gasoline, insurance, and maintenance—and local public transportation. I also include a variable that represents expenditures on all other goods and services, and this variable uses the CPI All Items Index as its price index.

2.2 Demand System Selection

The process of estimating the effects of changes in demand for certain products, such as communications goods and services, begins with the estimation of demand equations derived from consumer choice theory. Numerous flexible demand systems have been proposed to estimate demand curves from consumer expenditure data. In order to determine the best way to model US aggregate consumer expenditure data, Fisher et al. (2001) performed an empirical comparison of eight commonly used demand systems: three locally flexible functional forms, the Generalized Leontief (Diewert, 1971), Translog (Christensen et al., 1975), and Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980) models; three effectively globally regular functional forms, the Full Laurent model (Barnett, 1983), the Quadratic Almost Ideal Demand System (QUAIDS) (Banks et al., 1997), and the General Exponential Form (Cooper and McLaren, 1996); and two semi-nonparametric models; the Fourier model (Gallant, 1981) and the Asymptotically Ideal Model (Barnett, 1998). Out of the eight models, the QUAIDS model stood out as being the superior choice for modeling household-level U.S. consumer expenditure data. When the QUAIDS model was tested, it demonstrated no violations of concavity, and it fit extreme expenditures in the data set better than any other model tested.

Significantly, Fisher et al. (2001) noted that while semi-nonparametric models allow for more price flexibility relative to income flexibility, QUAIDS allows for more income flexibility relative to price flexibility. Therefore, while aggregate data may favor semi-non-parametric methods due to their superior forecasting performance, household-level data, which requires a greater level of income flexibility due to the wide range of incomes found in the sample, may be better modeled with the QUAIDS model. Therefore, I used the QUAIDS model for this research.

The Quadratic Almost Ideal Demand System (QUAIDS) model (Banks et al., 1997) was developed to address the need for a demand system that allows for non-linear Engel curves. Murray (2012) notes that the model upon which QUAIDS is based, the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980), is flexible enough to approximate demand functions for both very specific topics, such as demand for soft drinks (Dhar et al., 2003), and aggregated categories of goods such as housing, clothing and food, an example of which is seen in Fan et al. (1995). However, the AIDS model requires that Engel curves be linear, meaning that the expenditure share must have a linear relationship to the logarithm of total expenditure.

For many goods this assumption is not realistic. Expenditure shares for certain goods can increase until a certain point as income increases, due to the "luxury" status of those goods, then start to decrease as the good becomes a "necessity" relative to other purchases. Regarding transportation expenditures, Taylor and Houthakker (2010) found that the aggregate expenditure elasticities for transportation were the highest of all 29 general expenditure categories surveyed, implying that transportation expenses are in some sense a luxury, despite some level of expenditure on transportation clearly being a necessity. Banks et al. (1997) found through an analysis of expenditure data from the United Kingdom that products such as food and fuel had approximately linear Engel curves, while products such as clothing and alcohol had a distinctly quadratic shape, first increasing then decreasing. Previous research based on British data indicates that transportation goods likely share this characteristic (Blundell et al., 1993) Additionally, ICT products and services—such as cellular phones, computers, and Internet service plans—as well as non-fuel transportation goods and services such as plane tickets and personal vehicle expenditures—intuitively seem more similar to clothing and alcohol than to food or fuel. Both food and fuel would be viewed as necessities at every income level, while products such as clothing or cellular phone plans would likely be viewed as a luxury by lower-income consumers and as a necessity by higher-income consumers. The significance of the coefficient of the quadratic term, λ, in my final QUAIDS results confirms that the quadratic term is necessary.

2.2.1 The QUAIDS Model

Since the QUAIDS model is based upon the AIDS model, an understanding of the AIDS model is required to derive a QUAIDS demand system. The AIDS model was designed by Deaton and Muellbauer (1980) to provide an approximation to any demand system that is consistent with economic theory and that can be aggregated across consumers. The model is based on the assumption of Price Independent Generalized Logarithmic (PIGLOG) preferences, which was shown by Muellbauer (1976) to be aggregable across consumers. As opposed to an earlier model by Gorman (1953) that aggregated consumers based on consumption, Muellbauer defines the representative consumer as being representative in expenditure shares. These preferences can be expressed as:

$$\log e(u, \mathbf{p}) = (1 - u) \log(a(\mathbf{p})) + u \log(b(\mathbf{p})) \tag{1}$$

Where $\mathbf{p}$ is the vector of prices and $\log e(u, \mathbf{p})$ is the natural log of the expenditure function needed to achieve a level of utility "u", $0 \leq u \leq 1$. The functions $a(\mathbf{p})$ and $b(\mathbf{p})$ represent the costs of achieving a certain level of utility. For preferences in the PIGLOG class, $b(\mathbf{p})$ is greater than $a(\mathbf{p})$ so expenditure will increase as utility increases from zero to one, therefore the function $a(\mathbf{p})$ is designed to represent the minimum expenditure needed for subsistence, while $b(\mathbf{p})$ represents the expenditures at the highest level of utility, which is when utility equals its maximum value of one (Deaton and Muellbauer, 1980). The AIDS model defines:

$$\log(a(\mathbf{p})) = \alpha_0 + \sum_i \alpha_i \log p_i + \frac{1}{2} \sum_j \sum_i \gamma_{ij} \log p_i \log p_j \tag{2}$$

$$b(\mathbf{p}) = \log(a(\mathbf{p})) + \beta_0 \prod_i p_i^{\beta_i} \tag{3}$$

Where p_i is the price of good i, and α_i and β_i are parameters. When placed into the above log expenditure equation, the log expenditure is:

$$\log e(u, \mathbf{p}) = \log(a(\mathbf{p})) + u\beta_0 \prod_i p_i^{\beta_i} \tag{4}$$

In order to obtain the expenditure share equation, one takes the partial derivative of (4) with respect to log price:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i u \beta_0 \prod_i p_i^{\beta_i} \tag{5}$$

Solving for the indirect utility function, where x equals total expenditure, results in the following indirect utility function:

$$\log v(\mathbf{p}, x) = \frac{\log x - \log(a(\mathbf{p}))}{\beta_0 \prod_i p_i^{\beta_i}} \tag{6}$$

Using (6), one obtains the AIDS model expenditure share equations:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log \left[\frac{x}{a(\mathbf{p})} \right] \tag{7}$$

Where $\sum \alpha_i = 1$, $\sum \beta_i = 0$, $\sum_i \gamma_{ij} = 0$, $\sum_j \gamma_{ij} = 0$, and $\gamma_{ij} = \gamma_{ji}$

The QUAIDS model adds an additional quadratic term to account for non-linear Engel curves caused by differences in expenditure shares among individuals at different income levels. The QUAIDS model nests both the AIDS model and the Translog model, but through the addition of the quadratic income term it allows goods to be luxuries at some levels but necessities at others. Banks et al. (1997) demonstrated that having an indirect utility function of the form below is necessary in order for an expenditure share equation in the form of (7) to have an additional quadratic log income term and still be aggregable across consumers:

$$\log v(\mathbf{p}, x) = \left[\left[\frac{\log x - \log(a(\mathbf{p}))}{\prod p_i^{\beta_i}} \right]^{-1} + \lambda(\mathbf{p}) \right]^{-1} \tag{8}$$

Using Roy's identity, and letting $\lambda(\mathbf{p}) = \sum \lambda_i \log p_i$, results in the QUAIDS expenditure share equation:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log(\frac{x}{(a(\mathbf{p})}) + \frac{\lambda_i}{\prod_i p_i^{\beta i}} \left[\log(\frac{x}{(a(\mathbf{p})}) \right]^2 \tag{9}$$

Where $\sum \lambda_i = 0$ in order for the expenditure shares to continue to add up to one after the quadratic term is introduced.

2.2.2 Demographic, Sample Selection, and Censoring Adjustments

Given that numerous demographic characteristics can potentially cause changes in consumer spending, I also incorporated demographic variables and time variables into the analysis. The relevant demographic variables are those that can be assumed to have an effect on consumer spending on ICT and/or transportation expenditures. I included Northeast, South, and Midwest dummy variables, which are defined as their respective census region, with the West being the omitted category. I included a dummy variable for households in metropolitan areas with a population size of over 4 million (as of the 2000 Census), and a variable for households living in rural areas, as defined by the Census. To account for both changes over time and cyclical effects on expenditure, I created one dummy for households with six months or more of expenditures before the December 2007 - June 2009 recession, and another for households with six months or more of expenditures after the recession. I also included dummy variables for each decade of age, with the age category being defined by the average age of the individual and spouse, and the omitted category being individuals aged 60 and older.. I also included a dummy variable for education, equal to one if anyone in the household had a post high-school education, and a dummy variable equal to one if there are children aged 17 or younger in the household. Due to the Consumer Expenditure Survey not stating which household member made the purchase, I did not include a dummy variable for sex, because in a household with opposite-sex partners, any purchase could have been made by either individual.

I incorporate demographic variables into the model using Ray's (1983) method of scaling the expenditure function to account for household characteristics:

$$e_h(\mathbf{P}, \mathbf{z}, u) = \overline{x_0}(\mathbf{z}) \times \Phi(\mathbf{P}, \mathbf{z}, u) \times e_r(\mathbf{P}, u) \tag{10}$$

Where $e_h(\mathbf{P}, \mathbf{z}, u))$ is the household's expenditure as a function of the price vector $\mathbf{P}$, the demographic vector $\mathbf{z}$, and utility u. $\overline{x_0}(\mathbf{z}) \times \Phi(\mathbf{P}, \mathbf{z}, u)$ scales the expenditure function to account for demographic characteristics, with $\overline{x_0}(\mathbf{z})$ representing the effect of demographic characteristics on total expenditure and $\Phi(\mathbf{P}, \mathbf{z}, u)$ representing the effect of those characteristics on relative expenditure and therefore must be homogeneous of degree zero in price and utility, while $e_r(\mathbf{P}, u)$ are the expenditure characteristics of a reference household.

The demographic-adjusted expenditure shares are:

$$w_{ih} = \frac{\partial \log e_h(\mathbf{P}, \mathbf{z}, u)}{\partial \log p_i} = w_{ir} + \frac{\partial \log \Phi(\mathbf{p}, \mathbf{z}, u)}{\partial \log p_i} \tag{11}$$

For the AIDS model, Ray defines $\overline{x_0}(\mathbf{z}) = 1 + \rho\mathbf{z}$ and $\Phi(\mathbf{p}, \mathbf{z}, u) = \exp\left(u \prod_j p_j^{\beta_j} \left[\prod_j p_j^{\eta_j} - 1\right]\right)$, where ρ and η adjust for changes in total and relative expenditure respectively. In order to allow relative expenditures to scale with both price and utility,$\sum \beta_i = \sum \eta_i = 0,$. To account for the additional variation in the QUAIDS model, Poi (2002) defines:

$$\log \Phi(\mathbf{p}, \mathbf{z}, u) = \frac{u \prod_j p_j^{\beta_j} \left[\prod_j p_j^{\eta_j} - 1\right]}{\frac{1}{u} - \sum \lambda_j \log p_j} \tag{12}$$

Which, when $\frac{\partial \log \Phi(\mathbf{p}, \mathbf{z}, u)}{\partial \log p_i}$ is added to the expenditure share equation using (9) as shown in (11), results in:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + (\beta_i + \eta_i' \mathbf{z}) \log(\frac{x}{\overline{x_0}(\mathbf{z}) a(\mathbf{p})}) + \frac{\lambda_i}{\prod_i p_i^{\beta_i} \prod_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z}) a(\mathbf{p})})\right]^2 \tag{13}$$

In order to correct for sample selection bias created by only including households who participated in all four quarters of the survey, I applied a two-stage Heckman (1979) sample selection bias correction.

Letting f_h be a binary variable equal to one if the household participated in all four quarters of the survey, the first stage probit is:

$$P(f_h = 1|\mathbf{g}) = \Phi(\mathbf{g}'\zeta) \tag{14}$$

Where $\mathbf{g}$ is a vector of variables, including average quarterly log household income, the "before recession" and "after recession" time variables, and demographic variables;ζ is a vector of parameters; and $\Phi(\mathbf{g}'\zeta)$ is the Cumulative Distribution Function (CDF) for the standard normal normal distribution. In addition to including all of the demographic variables that I included in the expenditure share equation itself, I included dummy variables for homeownership, equal to one if the respondent is a homeowner, and for marital status, equal to one if the respondent is married. Both homeownership and marriage should decrease the probability of a person moving, and therefore being removed from the survey, but not affect spending on the goods included in the expenditure share equations. The results of the probit estimates indicate that both marital status and homeownership do have statistically-significant positive effects on the probability of homeownership.

I then take the standard normal Probability Density Function (PDF) of the above probit model, $\phi(\mathbf{g}'\zeta)$,and obtain the inverse Mill's ratio $\frac{\phi(\mathbf{g}'\zeta)}{\Phi(\mathbf{g}'\zeta)}$. I then add the inverse Mill's ratio as a variable in each expenditure share equation, multiplied by a parameter θ for each good i, resulting in the following expenditure share equation:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + (\beta_i + \eta_i'\mathbf{z}) \log(\frac{x}{\overline{x_0}(\mathbf{z})a(\mathbf{p})}) + \frac{\lambda_i}{\prod_i p_i^{\beta i} \prod_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z})a(\mathbf{p})})\right]^2 + \theta_i \frac{\phi(\mathbf{g}'\zeta)}{\Phi(\mathbf{g}'\zeta)} \quad (15)$$

In addition to adjusting for selection into all four interviews, it is necessary to adjust for the bias created by the large number of zero expenditures in each category of goods. In order to correct for this, I use the approach of Shonkwiler and Yen (1999). This approach has been used by others in estimating the censored QUAIDS model, including Lambert et al. (2006). Shonkwiler and Yen demonstrated that, simply adding the inverse Mill's ratio to the expenditure share equation—as I did for sample selection above—is incorrect for a situation in which the households with zero expenditures are included in the calculation, as is the case when there is a censored dependent variable. Therefore, given the observed expenditure share equation w_{ih}, the latent expenditure share equation w_{ih}^* equal to equation (15) above and the probit selection equation $d_{ih} = \mathbf{j_i}'\kappa + v_{ih}$, which represents whether household h had any expenditures on good i, the conditional expected value of the observed expenditure share is:

$$E(w_{ih}) = \begin{cases} w_{ih}^* + \xi_i \frac{\phi(\mathbf{j_i}'\kappa)}{\Phi(\mathbf{j_i}'\kappa)} & if\, \mathbf{j}'\kappa + v_{ih} > 0 \\ 0 & if\, \mathbf{j}'\kappa + v_{ih} \leq 0 \end{cases} \quad (16)$$

Where $\mathbf{j}$ is a vector of log price, log total expenditure, and demographic variables, κ is a vector of parameters, and v_{ih} is the error term. Because the probability of having positive expenditure for good i is $\Phi(\mathbf{j}'\kappa)$, given the assumption that having positive expenditure is independent of the sample selection equation in (14), the unconditional expected value for the expenditure share and the equation that I estimate for each good i is:

$$w_i = \Phi(\mathbf{j_i}'\kappa) \cdot \left(\alpha_i + \sum_j \gamma_{ij} \log p_j + (\beta_i + \eta_i'\mathbf{z}) \log(\frac{x}{\overline{x_0}(\mathbf{z})a(\mathbf{p})}) + \frac{\lambda_i}{\prod_i p_i^{\beta i} \prod_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z})a(\mathbf{p})})\right]^2 + \theta_i \frac{\phi(\mathbf{g}'\zeta)}{\Phi(\mathbf{g}'\zeta)} \right) + \xi_i \frac{\phi(\mathbf{j_i}'\kappa)}{\Phi(\mathbf{j_i}'\kappa)} \quad (17)$$

2.2.3 Elasticity Calculations

The elasticities of the non-censored QUAIDS model in (15) are calculated by first differentiating the expenditure share equations for good i with respect to $\log x$ and $\log p_j$ to obtain the terms μ_{ix} and μ_{ij}, then by which will then be used in the calculations (Banks et al., 1997). With the demographic adjustments, the derivatives are:

$$\mu_{ix} = \frac{\partial w_i}{\partial \log x} = \beta_i + \eta' \mathbf{z} + \frac{2\lambda_i}{\prod\limits_i p_i^{\beta i} \prod\limits_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z}) a(\mathbf{p})}) \right] \tag{18}$$

$$\mu_{ij} = \frac{\partial w_i}{\partial \log p_j} = \gamma_{ij} - \mu_{ix} \cdot \left(\alpha_j + \sum_{k=1}^{n} \gamma_{jk} \log p_j \right) - \frac{(\beta_j + \eta_j' \mathbf{z})\lambda_i}{\prod\limits_i p_i^{\beta i} \prod\limits_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z}) P}) \right]^2 \tag{19}$$

The formulas for the elasticities are then as follows, with e_{ix} being the expenditure elasticity, e_{ij} being the uncompensated price elasticity for good i with respect to price j, and δ_{ij} being the Kronecker δ, equal to one if $i = j$ and zero otherwise:

$$e_{ix} = \frac{\partial w_i}{\partial \log x} \cdot \frac{1}{w_i} + 1 = \frac{\mu_{ix}}{w_i} + 1 \tag{20}$$

$$e_{ij} = \frac{\partial w_i}{\partial \log p_j} \cdot \frac{1}{w_i} - \delta_{ij} = \frac{\mu_{ij}}{w_i} - \delta_{ij} \tag{21}$$

In order to calculate the elasticities of the censored model, I used the method of Yen, Kan, and Su (2002) and calculated the elasticities using the *expected value* of the expenditure share equation (17). I therefore calculated $\hat{\mu}_{ix}$ and $\hat{\mu}_{ij}$ as:

$$\hat{\mu}_{ix} = \frac{\partial E(w_i)}{\partial \log x} = \Phi(\mathbf{j_i'}\kappa) \cdot \left(\beta_i + \eta' \mathbf{z} + \frac{2\lambda_i}{\prod\limits_i p_i^{\beta i} \prod\limits_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z}) a(\mathbf{p})}) \right] \right) \tag{22}$$

$$\hat{\mu}_{ij} = \frac{\partial E(w_i)}{\partial \log p_j} = \Phi(\mathbf{j_i'}\kappa) \cdot \left(\gamma_{ij} - \hat{\mu}_{ix} \cdot \left(\alpha_j + \sum_{k=1}^{n} \gamma_{jk} \log p_j \right) - \frac{(\beta_j + \eta_j' \mathbf{z})\lambda_i}{\prod\limits_i p_i^{\beta i} \prod\limits_i p_i^{\eta_i' z}} \left[\log(\frac{x}{\overline{x_0}(\mathbf{z}) P}) \right]^2 \right) \tag{23}$$

This results in the following elasticity equations:

$$e_{ix} = \frac{\partial E(w_i)}{\partial \log x} \cdot \frac{1}{E(w_i)} + 1 = \frac{\hat{\mu}_{ix}}{E(w_i)} + 1 \tag{24}$$

$$e_{ij} = \frac{\partial E(w_i)}{\partial \log p_j} \cdot \frac{1}{E(w_i)} - \delta_{ij} = \frac{\hat{\mu}_{ij}}{E(w_i)} - \delta_{ij} \tag{25}$$

I estimated the expenditure share equations using iterated feasible generalized least squares estimation of a seemingly unrelated regression model, which requires the selection of a value for the constant α_0. Given that the level of expenditure needed to achieve the subsistence level of utility is represented by the price index $a(\mathbf{p})$, the minimum value of observed log expenditure is the upper bound for the value of α_0 (Banks et al., 1997). Therefore, I set α_0 equal to 7.29, which is just below the smallest log expenditure value in the sample. Using the price of each product category in the index, I estimated the ρ vector of demographic parameters, the η demographic parameter matrix, the α_i and γ_{ij} for all product categories, the β_i parameters for the log of total expenditure divided by the price index, the λ_i parameters which, after being divided by $\prod_i p_i^{\beta i} \prod_i p_i^{\eta_i' z}$, serve as the coefficients for the log of squared expenditure divided by the price index, the θ_i coefficients on the inverse Mill's ratio for the sample selection term, and ξ_i coefficients on the inverse Mill's ratio for the censoring adjustment.

Based on the prior literature, my assumption was that technology expenditures would have an effect on transportation, but the effect would vary based on the forms of technology and transportation. While unfortunately the data that I am using do not distinguish between reasons for travel, I predicted that technology would serve as a substitute for local forms of transportation, due to the substitution of telecommuting and teleshopping for commuting to work and for shopping. However, based on the likely complementary relationship of technology and leisure travel, I predicted that technology expenditures would increase expenditures on long-distance travel.

3 Results[1,2]

The results from my expenditure share estimations demonstrate that the relationship between information technology and transportation is complex and varies with the forms of technology and transportation. Due to the potential for outliers to considerably affect the magnitude of the elasticities in certain categories such as airfare, I used the median expenditure and cross-price elasticities in my analysis. The statistical significance of the beta and lambda income coefficients, shown in Table 2, confirmed the importance of including the quadratic terms in the model, and demonstrated that total expenditure, and therefore income, is a significant determinant of expenditure shares for the majority of the goods. The median expenditure elasticities, shown in Table 3, were generally consistent with expectations. Both air travel and other intercity transportation were highly expenditure elastic, which would be consistent with intercity travel being somewhat of a luxury and therefore more common as total expenditure increases. Private transportation was close to unit expenditure elastic, which is reasonable given the central role that private transportation plays at all levels of income, along with the opportunities to travel likely increasing with income. Local public transportation was highly expenditure inelastic, which given that one would not expect individuals to greatly increase local public transportation use with total expenditure, is consistent with expectations. While computers were expenditure inelastic, which would seem somewhat surprising, both the β and λ income coefficients were statistically insignificant. Internet and cellular phones were both expenditure inelastic, which given that internet and cellular phone service often come in predefined packages, often with unlimited use of certain services, expenditure on these services may not increase considerably with income. Additionally, the significance of the sample selection and censoring correction coefficients, shown in Table 4, indicated the importance of including those terms in the model to avoid an omitted variable bias.

[1]The QUAIDS coefficient estimates that are not displayed in the text are included in the appendix, as well as the results of the first-stage probit estimations

[2]When estimating the model, I also included an eighth category for all other goods, in order to account for the effect of total expenditure, rather than just expenditures on a few goods, on expenditures in the categories of interest. The conditions given earlier, that $\sum \alpha_i = 1$, $\sum \beta_i = 0$, $\sum_i \gamma_{ij} = 0$, $\sum_j \gamma_{ij} = 0$, $\gamma_{ij} = \gamma_{ji}$, and $\sum \eta_i = 0$, allow one to calculate most of the coefficients for the eighth category directly from the coefficients provided for the other seven categories. Therefore, because the elasticities between the categories of interest and the "all other goods" category are not relevant for my analysis, I did not include estimates for that category in any of the tables. I can provide those estimates upon request.

Table 2: QUAIDS Income Coefficient Estimates

	Air Travel	Other Intercity Trans.	Private Trans	Local Public Trans	Computers	Internet	Cell
Beta	0.0097***	0.0011	-0.0505***	0.0021**	-0.0015	-0.0024***	-0.0010
	(0.0011)	(0.0011)	(0.0024)	(0.0010)	(0.0012)	(0.0005)	(0.0008)
Lambda	-0.0011***	-0.0010***	-0.0160***	0.0023***	0.0005	0.0002*	0.0006***
	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0001)	(0.0002)
*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses							

Table 3: Median Expenditure Elasticities

Airfare	Other Intercity	Priv. Trans	Local PT	Computers	Internet	Cell
1.966	1.956	1.106	0.369	0.775	0.504	0.744

Table 4: QUAIDS Sample Selection and Censoring Correction Coefficients

	Air Travel	Other Intercity Trans.	Private Trans	Local Public Trans	Computers	Internet	Cell
Theta	-0.0043***	-0.0111***	-0.0205***	0.0197***	0.0022	-0.0032***	0.0067***
	(0.0013)	(0.0012)	(0.0022)	(0.0013)	(0.0013)	(0.0004)	(0.0009)
Xi	0.0215***	0.0075***	0.1115***	-0.0060***	0.0044***	0.0017**	0.0126***
	(0.0015)	(0.0018)	(0.0016)	(0.0009)	(0.0014)	(0.0008)	(0.0014)
*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses							

Table 5: QUAIDS Gamma Coefficient Estimates

	Air Travel	Other Intercity Trans	Private Trans	Local Public Trans	Computers	Internet	Cell Phones
Air Travel	-0.0189*	-0.0109	0.0297***	0.0269***	-0.0017	-0.0064**	0.0045
	(0.0114)	(0.0087)	(0.0092)	(0.0090)	(0.0034)	(0.0026)	(0.0091)
Other Intercity Trans		-0.0052	0.0034	0.0359***	-0.0130***	0.0081***	0.0299***
		(0.0122)	(0.0080)	(0.0095)	0.0037	0.0030	0.0104
Private Trans			-0.0103	-0.0192**	0.0147***	-0.0003	-0.0414***
			(0.0123)	(0.0083)	(0.0039)	(0.0025)	(0.0100)
Local Public Trans				-0.0276**	0.0078**	-0.0010	-0.0135
				(0.0120)	(0.0035)	(0.0028)	(0.0101)
Computers					0.0033	-0.0045***	0.0188***
					0.0024	(0.0014)	(0.0049)
Internet						-0.0011	-0.0063**
						(0.0014)	(0.0026)
Cell Phones							-0.0998** *
							(0.0214)
*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses							

Table 6: Median Uncompensated Price Elasticities

	Air Travel	Other Intercity Trans.	Private Trans	Local Public Trans	Computers	Internet	Cell
Air Travel	-2.308	-0.754	1.895	1.847	-0.117	-0.439	0.307
Other Intercity Trans	-1.823	-1.878	0.396	5.978	-2.165	1.340	4.970
Private Trans	0.183	0.021	-1.111	-0.115	0.089	-0.003	-0.254
Local Public Trans	1.873	2.496	-1.191	-2.915	0.546	-0.066	-0.932
Computers	-0.125	-0.982	1.158	0.594	-0.753	-0.342	1.422
Internet	-0.981	1.253	0.028	-0.153	-0.699	-1.174	-0.969
Cell	0.219	1.426	-1.933	-0.643	0.895	-0.298	-5.756

All of the own-price elasticity estimates were negative, as seen in Table 6, which is what one would expect for the estimates to be consistent with theory. The relationships among different forms of transportation were mostly, but not entirely, consistent with expectations. Air travel was found to be a substitute for both private transportation and local public transportation, with the gamma price coefficients, which can be found in Table 5, being statistically significant for both. Air travel and other intercity transportation were found to be complements, which is the opposite of what one would expect, but the gamma price coefficient was not statistically significant. Other intercity transportation was found to be a substitute for private transportation and local public transportation, with the gamma coefficient being statistically significant for local public transportation. However, private transportation was found to be a complement for local public transportation, with a significant gamma coefficient, which is the opposite of what one would expect. The relationships among information technology categories were generally consistent with expectations, with internet service being a complement for both computers and cellular phones. However, computers and cellular phones were found to be substitutes. All of the technology relationships had statistically significant gamma coefficients.

The relationship between information technology and transportation varied by the type of information technology and form of transportation. Computers were complements for air travel and other intercity transportation, but substitutes for private transportation and local public transportation, with the gamma price coefficients being significant for all of the transportation forms except for air travel. Internet service was a substitute for other intercity transportation, but a complement for air travel and local public transportation, with the gamma coefficients being statistically significant for air travel and other intercity transportation. The statistical insignificance of the relevant gamma term and the near-zero value of the elasticity of private transportation with respect to internet price, and internet with respect to private transportation price, indicate that no relationship between internet service and private transportation was found. Cellular service was found to be a substitute for air travel and other intercity transportation, but a complement for private transportation and local public transportation, with the gamma coefficients being statistically significant for other intercity transportation and private transportation.

4 Conclusion

The elasticities found through applying the QUAIDS model show that the relationship between technology and transportation is complex. Computers were substitutes for private transportation, indicating that consumers may substitute computer-based activity for transportation. The lack of either a substitution or a complementary relationship between home internet and private transportation may provide additional support for prior research indicating that the relationship between ICT and transpiration varies depending on the purpose of travel. Home Internet was a complement for air travel, which could be related to the internet easing the process of arranging air travel. Cellular phones were complements for private transportation and local public transportation, which seems plausible since individuals who travel more often may be more likely to spend more on cellular service in order to have access to Internet and phone service "on-the-go". Of course, causality could run the other direction as well, with individuals using cellular phones to arrange activities requiring travel. This may indicate that as mobile internet devices become more prevalent relative to home-based internet devices, ICT may serve as more of a complement for private transportation rather than a substitute. This indicates that technology may not have the desired effect of reducing the negative externalities associated with transportation use. Therefore, as mobile technology continues to increase, transportation networks could become further strained, a concern that may be relevant for governments when planning for future transportation use. The relationship between technology expenditure categories is also interesting, and the substitution relationship between computers and cellular phones may indicate that, as cellular phones and other mobile devices become more common, consumers may spend less on computers.

Future directions for research would include relating the time spent using technology to technology expenditures, since expenditures on internet and cellular phones do not precisely measure the use of these devices given the existence of fixed plans. It would also be useful to be able to distinguish between reasons for travel, to determine if the effect of technology use varies by reason for travel or distance traveled. Also, as tablets become more prevalent, it would be interesting to see how the effect of their use compares to that of computers and cellular phones. Analyzing these issues could help clarify the effect of technology on consumers' transportation decisions.

Acknowledgments

I thank Dennis Coates for his excellent guidance and advice throughout the process of writing this paper, Christelle Viauroux for providing helpful advice, and the participants at the US Consumer Expenditure Survey Microdata Users' Workshop for their useful comments and suggestions.

Appendix

A QUAIDS Coefficient Estimates

Table A.1: QUAIDS Alpha Coefficient Estimates

	Air Travel	Other Intercity Trans.	Private Trans.	Local Public Trans.	Computers	Internet	Cell
Alpha	0.0181*	0.0395***	0.0807***	-0.0034	0.0184***	-0.0079**	-0.1057***
	0.0107	0.0115	0.0126	0.0113	0.0060	0.0033	0.0220
*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses							

Table A.2: QUAIDS Demographic Coefficient Estimates

	Rho	Eta Air Travel	Eta Other Intercity Trans.	Eta Private Trans	Eta Local Public Trans.	Eta Computers	Eta Internet	Eta Cell
Under 35	1.4208***	-0.0040***	-0.0018***	-0.0168***	0.0033***	0.0006	0.0010***	-0.0018***
	(0.1438)	(0.0006)	(0.0005)	(0.0010)	(0.0003)	(0.0006)	(0.0002)	(0.0004)
Thirties	0.7524***	-0.0017***	-0.0003	-0.0085***	0.0010***	0.0000	0.0006***	-0.0026***
	(0.0784)	(0.0004)	(0.0003)	(0.0007)	(0.0003)	(0.0004)	(0.0001)	(0.0003)
Forties	0.5215***	-0.0005	0.0006**	-0.0079***	-0.0002	-0.0001	0.0005***	-0.0030***
	(0.0606)	(0.0003)	(0.0003)	(0.0006)	(0.0003)	(0.0004)	(0.0001)	(0.0003)
Fifties	0.4873***	-0.0003	0.0009***	-0.0079***	-0.0012***	0.0004	0.0005***	-0.0022***
	(0.0545)	(0.0003)	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0001)	(0.0002)
Has	-0.0595	0.0011***	0.0010***	-0.0004	-0.0018***	0.0004*	-0.0001	-0.0009***
Children	(0.0476)	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Has Post-HS	-0.2588***	-0.0008***	0.0000	0.0009**	0.0007***	-0.0003	-0.0004***	0.0003***
Education	0.0262	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Rural	0.1288**	0.0025***	0.0008**	-0.0081***	-0.0032***	0.0002	0.0002**	0.0006***
	(0.0562)	(0.0004)	(0.0004)	(0.0007)	(0.0004)	(0.0004)	(0.0001)	(0.0002)
City with	0.3029***	-0.0019***	-0.0005***	0.0050***	0.0001	-0.0003*	0.0003***	0.0002*
pop. > 4 mil.	(0.0340)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Northeast	0.2280***	-0.0006**	-0.0001	0.0052***	-0.0016***	0.0000	0.0000	0.0011***
	(0.0410)	(0.0003)	(0.0002)	(0.0005)	(0.0002)	(0.0003)	(0.0001)	(0.0001)
South	0.1411***	0.0006***	0.0001	-0.0029***	-0.0006***	0.0005**	0.0001	-0.0004***
	(0.0344)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
West	-0.0330	-0.0026***	-0.0004*	0.0035***	0.0018***	-0.0004	0.0000	0.0007***
	(0.0340)	(0.0002)	(0.0002)	(0.0005)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Before	-0.1046***	-0.0002	-0.0002	0.0008	0.0010***	-0.0001	0.0000	0.0005***
Recession	(0.0282)	(0.0004)	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0001)	(0.0002)
After	0.2185***	-0.0015***	-0.0020***	-0.0055***	0.0036***	0.0006	-0.0009***	-0.0002
Recession	(0.0405)	(0.0005)	(0.0004)	(0.0007)	(0.0004)	(0.0005)	(0.0002)	(0.0003)

*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses

B First-Stage Probit Estimates

Table B.1: Probit Estimates for Participation in All Four Interviews

	Coef.		Coef.
Under30	-0.6884***	Rural	0.0659***
	(0.0184)		(0.0231)
Thirties	-0.3850***	City with pop. > 4 mil.	0.0450***
	(0.0182)		(0.0117)
Forties	-0.2432***	Northeast	0.0032
	(0.0169)		(0.0169)
Fifties	-0.1026***	South	-0.0557***
	(0.0158)		(0.0138)
Homeowner	0.4415***	West	-0.0578***
	(0.0124)		(0.0153)
Married	0.0780***	Before recession	-0.0719***
	(0.0118)		(0.0170)
Has Post-HS Education	-0.0127	After recession	-1.1352***
	(0.0114)		(0.0151)
Has Children	0.0870***	Average expenditure per quarter	-8.96E-08
	(0.0137)		(6.30E-07)
		Constant	0.5338***
			(0.0217)
*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses			

Table B.2: Probit Estimates for Non-Zero Expenditures

	Air Travel	Other Intercity Trans.	Private Trans.	Local Public Trans.	Computers	Internet	Cell
ln air price	-1.0107	0.2795	1.8394	-0.3472	1.4468	-5.4199***	-2.5606
	(1.6001)	(1.7141)	(2.9169)	(1.7258)	(1.6788)	(1.5686)	(1.5826)
ln other IC	2.6479*	1.0460	-2.2431	2.0117	-2.3171	6.7056***	1.7922
trans. price	(1.5113)	(1.6131)	(2.7606)	(1.6186)	(1.5761)	(1.4892)	(1.5051)
ln private	1.6809*	1.2020	-0.7199	0.6674	-0.2597	2.6524***	2.0776**
trans. price	(0.9633)	(1.0406)	(1.8010)	(1.0409)	(0.9899)	(0.8884)	(0.9782)
ln local public	3.5077	0.9994	1.5063	2.3850	0.2075	10.5521***	8.0371*
trans. price	(4.1614)	(4.4404)	(7.6150)	(4.4820)	(4.3620)	(4.0408)	(4.1376)
ln computer	0.3968	-0.0372	0.8717	0.1158	-0.4501	1.0977	1.2958
price	(1.4937)	(1.5951)	(2.7322)	(1.6112)	(1.5653)	(1.4467)	(1.4853)
ln internet	0.2393	0.3115	0.0346	-0.4443	0.2385	-0.5263*	-0.7571**

price	(0.3333)	(0.3564)	(0.6092)	(0.3587)	(0.3484)	(0.3167)	(0.3337)
ln cell price	5.0172	2.0708	4.7960	-1.4799	2.2752	8.7459***	4.6004
	(3.3014)	(3.5383)	(6.0701)	(3.5502)	(3.4311)	(3.1281)	(3.3201)
ln all items	-3.3373	-4.0028	2.6090	-6.2287	-1.0318	6.2272	-0.7853
index	(5.9606)	(6.3840)	(10.9245)	(6.4125)	(6.1754)	(5.6528)	(6.0021)
ln total	0.8881***	0.6328***	1.3436***	-0.0717***	0.6374***	0.5369***	0.7203***
expenditure	(0.0152)	(0.0156)	(0.0288)	(0.0143)	(0.0154)	(0.0134)	(0.0141)
Under 30	0.0095	-0.0264	0.0039	0.4168***	0.2730***	0.0240	0.6821***
	(0.0307)	(0.0333)	(0.0547)	(0.0319)	(0.0321)	(0.0291)	(0.0316)
Thirties	-0.0993***	-0.1174***	-0.1345**	0.2790***	0.1920***	0.1213***	0.5185***
	(0.0281)	(0.0302)	(0.0525)	(0.0300)	(0.0292)	(0.0264)	(0.0286)
Forties	-0.1156***	-0.1152***	0.0123	0.2361***	0.1862***	0.1637***	0.4115***
	(0.0255)	(0.0274)	(0.0479)	(0.0276)	(0.0268)	(0.0239)	(0.0252)
Fifties	-0.0802***	-0.0586**	0.0319	0.2236***	0.0943***	0.1819***	0.3257***
	(0.0230)	(0.0244)	(0.0419)	(0.0252)	(0.0248)	(0.0217)	(0.0224)
Has children	-0.3319***	-0.2740***	0.0682	-0.0851***	-0.0170	0.1165***	-0.0406*
	(0.0213)	(0.0229)	(0.0454)	(0.0224)	(0.0213)	(0.0198)	(0.0223)
Has post-HS	0.3418***	0.2605***	0.2269***	0.0691***	0.2620***	0.2169***	0.0573***
education	(0.0191)	(0.0211)	(0.0316)	(0.0202)	(0.0203)	(0.0174)	(0.0178)
Rural	-0.1657***	-0.1039**	0.2662***	-0.2290***	0.0583	0.1392***	-0.0596*
	(0.0369)	(0.0401)	(0.0716)	(0.0451)	(0.0365)	(0.0318)	(0.0322)
City with	0.0361**	-0.0150	-0.6146***	0.5159***	-0.0750***	0.0763***	-0.0079
pop > 4 mil	(0.0178)	(0.0191)	(0.0335)	(0.0187)	(0.0188)	(0.0170)	(0.0184)
Northeast	-0.0570**	-0.0164	-0.6510***	0.2949***	-0.0809***	0.0922***	-0.1424***
	(0.0253)	(0.0271)	(0.0444)	(0.0262)	(0.0266)	(0.0240)	(0.0255)
South	-0.1901***	-0.1677***	0.0556	-0.2412***	-0.1211***	0.0480**	0.0171
	(0.0215)	(0.0233)	(0.0431)	(0.0246)	(0.0222)	(0.0200)	(0.0211)
West	0.2698***	0.1622***	-0.1521***	0.2789***	0.0175	0.0297	-0.0003
	(0.0229)	(0.0243)	(0.0482)	(0.0247)	(0.0239)	(0.0222)	(0.0240)
Before	-0.0302	-0.0137	0.1830*	-0.1458*	0.1088*	0.0246	-0.1257**
recession	(0.0580)	(0.0632)	(0.1046)	(0.0622)	(0.0616)	(0.0535)	(0.0579)

After recession	0.0355 (0.0795)	0.0841 (0.0867)	0.0619 (0.1480)	0.0258 (0.0864)	-0.0225 (0.0814)	-0.0355 (0.0723)	0.0204 (0.0800)
Constant	-51.6028 (60.5353)	-14.6617 (64.5844)	-53.3230 (110.7506)	15.5262 (65.3483)	-7.0105 (63.5464)	-153.9286*** (59.3262)	-74.4240 (59.9518)
*p < 0.10, ** p <0.05, *** p<0.01. n = 32,459, standard errors in parentheses							

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