**Just Pricing: Comparing the Effects of Congestion Pricing and Transportation Sales Taxes on Low-Income Households**

**By L.A. C.  Schweitzer and Brian D. Taylor**

L.A.C.  Schweitzer, Corresponding author
Assistant Professor
Urban Affairs and Planning
Virginia Tech University
208 Architecture Annex
Blacksburg, VA 24060
lschwei@vt.edu

and

Brian D. Taylor
Associate Professor of Urban Planning
UCLA Institute of Transportation Studies
3250 Public Policy Building
Los Angeles, CA 90095-1656
btaylor@ucla.edu

**Abstract.** Those who oppose congestion pricing on roads frequently argue that low-income, urban residents will suffer disproportionately if tolled to use congested freeways, either through higher out-of-pocket costs for travel and/or by diverting, delaying, or discontinuing trips. Too often, however, this assertion is made in the abstract, without considering 1) how much impoverished residents currently pay for transportation through fuel and sales taxes or 2) how much impoverished residents would pay for highway infrastructure under an alternative revenue-generating schema, such as an increased sales tax. And while increased local sales taxes are among the faster growing forms of transportation revenues in the U.S., they are rarely criticized on social equity grounds. In this paper, we compare the cost burden of an existing congestion-priced high-occupancy/toll facility on State Route 91 (SR91) in Orange County, California, with the cost burden of Orange County's local option transportation sales tax. We use Consumer Expenditure Survey data and user information from the SR91 project to model expenditures by income group. We use these models to estimate the cost burden by income group for both sales taxes and congestion charges. We find that although the sales tax spreads the costs of transportation facilities across a large number of people, it redistributes an estimated $3 million (USD) per year from less affluent residents to those with higher incomes. Given these results, we conclude that the increasingly popular U.S. trend of user local option sales taxes to fund transportation improvements conflict with both environmental and equity improvements in transport policy and finance.

## INTRODUCTION

In recent years, many activists, transportation analysts, and policy makers have questioned the equity of transportation finance, particularly pricing. Over the past decade, high-profile civil rights lawsuits have been filed against public transit operators over fare increases thought to disproportionately burden the poor [1, 2]. Similarly, transportation justice critiques have been leveled against many congestion-, or value-, priced road facility proposals [3, 4]. While congestion-/ value-pricing has long been touted by transportation economists as an ideal way to improve the efficiency of highway systems, skeptics have rightfully questioned whether the costs of these efficiency gains would be disproportionately paid by the poor [5, 6].

Skeptics of road pricing appear to assume, however, that tolls force low-income drivers to pay for something for which they would otherwise pay nothing. Transportation facilities, if they are to be built and maintained, have to be paid for somehow, and they are paid for in the U.S. via gas taxes, vehicle registration fees, and sales taxes. All of these affect the poor. Dill et al. (1999) demonstrated, for example, that existing methods of transportation finance have varied effects by race and by class in California [7]. They found that the most progressive tax or user charge was the vehicle registration fee, as the fee in California varies by the value of the vehicle that, in turn, is positively correlated with income. Further, local option sales taxes for transportation, which have increased significantly in number over the past two decades, are regressive with respect to both income and transportation system use [8]. While the fuel tax is regressive with respect to income, it is progressive with respect to highway use because those who drive more and who drive larger, heavier vehicles tend to use more fuel. In contrast, the sales tax is both income regressive and is largely unrelated to transportation system use.

Thus, the relevant equity question regarding congestion-/value-pricing is not whether such congestion charges are regressive in the abstract, but whether congestion tolls are more or less regressive than other methods of paying for transport infrastructure and operation. This is the question that we examine in this paper.

This question of relative equity in transportation finance takes on enormous significance given several compounding trends in mobility and urbanization. Inflation-adjusted government revenues for transportation increasingly lag continuing growth in vehicle travel. Federal, state, regional, and local governments thus face difficult choices for how to pay for building, operating, and maintaining transportation networks to accommodate increasing travel, particularly in large and rapidly growing metropolitan areas. As vehicle travel and, especially, goods movements have increased dramatically in recent years, and the relationship between motor fuels tax revenues collected and total miles driven has weakened. Three factors combine to make it difficult for fuels taxes to keep up with expanding needs: increasing vehicle fuel efficiency, the fact that per-gallon fuel tax revenues do not increase with inflation, and increasing transportation program commitments [9, 10]. Under this triple threat, motor fuel tax revenues account for a progressively smaller portion of overall transportation revenues. How policy-makers chose to supplement the gas tax portends substantial consequences for equity, environmental, and mobility goals.

The next section of this paper examines both the theoretical and general empirical findings on the cost burden of road finance schemes. The third section outlines our analysis of a case study in Orange County, California. We estimate and compare the costs for various income groups under both a plausible, hypothetical sales tax and an existing value pricing scheme. We find that a sales tax scheme would disperse the costs of the facility widely; as a result low-income households under sales tax regimes provide substantial cost savings to the more-affluent-than-average SR91 users.

**BACKGROUND**

We begin by defining several concepts central to this analysis. *Cost burden* is the amount paid by an individual, household, or group. *Progressivity* means that the ratio of the tax burden to income increases with income; *regressivity* is the opposite. In most tax incidence research the concepts of progressivity or regressivity typically relate to income, while in transportation they can also pertain to the costs imposed or the benefits received from transportation services, policies, or taxes.

*Road pricing* refers to the practice of charging for facility use, and there are many options for implementing road pricing. A *congestion charge* is a fee applied to a capacity-constrained facility, which rations road space by charging a fee that prompts at least some drivers to forego the trip entirely or to travel on a different route, at another time, on a different mode. Congestion pricing works by eliminating trips that drivers do not value enough to pay their full marginal social cost. By using variable tolls to ration scarce road space that is not currently priced directly, many fear that the increased out-of-pocket costs of road pricing would cause impoverished drivers to be “priced off the road” [11].

By contrast, most *value pricing* schemes price only part of a multiple-lane facility, giving drivers the option of paying to use uncongested toll lanes or taking their chances with traffic in the unpriced lanes.  On many of these facilities, carpoolers can use the priced lane for free or at a reduced rate; these facilities are *High-Occupancy/Toll* or *HOT-lanes*. Richardson and Bae (1992) argue that value-priced facilities like SR91 are by design consistent with equity goals, because drivers always have the option to remain in the free lane rather than pay into the faster lane [12]. Others are not so sanguine.

As countries around the world have implemented different types of congestion and value pricing schemes, the evidence suggests that individuals vary significantly in their willingness to seek out the benefits of a value-priced facility and how able they are to avoid the costs of a general cordon or a congestion charge. The ultimate consequences of road pricing schemes, in turn, vary significantly according to geographic context as well as driver preferences and resources.

First, the effects of any pricing scheme on a road network depend on the geospatial distribution of travelers, the transportation network characteristics, and the configuration of potential destinations. Because U.S. cities—as well as most cities internationally—are often segregated spatially by race and by class, the sociodemographic make-up travelers on one set of individual links of the transportation network may be quite different from travelers in another part of the network. Similarly, the distribution of work and residential opportunities across regions can, at least in theory, induce different population segments to travel habitually along different parts of the network [3, 13-19].

Second, while decisions to opt onto a value-priced facility can vary systematically by driver and household characteristics, such choices also vary significantly for the same individual or household from day-by-day and even trip-by-trip. Small (1992) argues, for example, that, for most people, the consequences of arriving early are less than those of being late [5]. Also, research has found that reliability matters significantly to travelers, more so than previously thought [20]. Li (2001) demonstrates that trips on the SR91, our case study facility, from home to recreation or leisure sites are 88 percent less likely than journey-to-work trips to use paid lanes. Shopping trips and personal trips are 60 to 67 percent less likely than commute trips to pay. She argues that the HOT lanes offer a “coming-home premium;” that is, contrary to Small’s arguments, SR91 users are almost twice as a likely to use HOT lanes from work to home than the other way, perhaps reflecting heavier afternoon traffic delays as well as the time-sensitive demands of childcare for working parents.

Thus the value of uncongested travel reflects both the public and private resources available to individual drivers. Mokhtarian and Raney (1997) theorize that different people have different abilities and strategies for dealing with congestion delays, such as buying cellular phones, mobile computers, good car stereos, and eating restaurant meals when a person is unable to get home quickly [21]. They found, using a factor analysis, that women were far more likely than men to engage in more expensive congestion delay mitigation measures, and that those with low incomes were less able to employ these types of time-savers to make up for time lost sitting in traffic.

On SR91, Sullivan (1998) finds that few people who acquire the electronic transponders that allow them to use the automated toll lanes on SR91 actually use the tolled facilities every day [22]. While usage of the congestion priced lanes tends to increase with household income, Sullivan finds that these facilities are not the “Lexus lanes” they were feared to be by some critics [23]. While relatively few of the drivers who acquired transponders on SR91 are from low-income households, Sullivan (2002) finds that relatively few peak hour highway users on any lanes—tolled or free—are from low-income households. About one-third of the corridor travelers from households with incomes below $40,000 use the lanes at least occasionally, compared to about two-thirds of travelers from households with incomes over $100,000 [24]. The decision to obtain the transponder needed to access SR91 also varies with education, language skills, and gender, with women more likely to sign up than men [25].

In short, the ultimate cost of a toll does not end with whether a low-income person chooses to pay the charge. Rather, congestion tolls are traded off against the consequences of late or delayed arrival, which does not always track with income, and willingness to pay the toll is contingent on the many monetary and time resources available to the household. Different public or private resources also influence the ability to shift the cost of the toll onto others, such as employers or customers, or whether travelers can avoid charges by moving to different modes, like public transit, as many did when London’s center city cordon congestion toll was introduced in YEAR [17, 26]. Thus, how a toll affects travel choice and household expenditures depends on a complex array of factors and is not a simple story of rich and poor. By contrast, a consensus has emerged that even with exemptions and even with some “backward shifting,” which we will discuss shortly, sales taxes are income regressive [27-30].

A sales tax is a consumption tax applied as a percentage of the pre-tax expenditure. One important trend has been an increasing reluctance by public officials to increase either fuel or property taxes for transportation in favor of small increases in sales taxes. For nearly a century, fuel taxes have been the principal source of revenues for highways, while property taxes have paid for most local streets [31]. Popular and political reticence about raising these taxes extends even to simple indexing of per diem fuel tax rates to account for either inflation or increasing fuel efficiencies [32]. So as fuel and property taxes increasingly have become politically off-limits, the gap between road system use and the generation of revenues to build, operate, and maintain this system have widened [33]. In response to these pressures, local governments in many states have turned to local option sales taxes [8]. In our case study area, so-called “Measure M” in Orange County is a 0.05-cent sales tax that has been used to fund freeway and other transportation improvements throughout the county [34].

As with tolls, economists theorize that sales taxes may be shifted either onto or away from the consumer. Sales taxes (again like tolls) change the relative out-of-pocket costs of goods. Depending on the natures of those goods and their production technologies, the burden of sales taxes can in theory be shifted forward onto consumers, backwards onto producers, or even onto the laborers who produce the taxed goods [35]. That is, sales taxes can simply add to the price of a good (forward shifting), or not increase the price of the good by shifting backward onto firms in the form of increased production costs, or onto workers in the form of reduced wages, or some combination of these. The net effect of a tax payment depends not only the size of the tax payment, but also on the supply and demand effects the tax induces. If, for example, the equilibrium price of a given item rises by the less than the tax payment, the supplier of the good pays a portion of the tax along with the consumer. Because the vendor may react by reducing inputs such as labor, the net cost may be both diffuse and far removed from the good's consumer. Sales taxes are often designed so that goods with the least elastic demand, such as food, fuel, or clothing, are taxed lightly or not at all. As a result, there may no strong *a priori* basis for assuming how much of a sales tax consumers will pay [27, 36].

Even so, many empirical analyses of tax incidence assume that sales taxes are shifted 100 percent, or more, onto consumers. Existing markets are characterized to varying degrees by imperfect competition; the comparative market power enjoyed by producers when competition is imperfect allows producers to shift the tax burden entirely onto consumers [37]. In a widely cited 1996 study, Poterba examined tax shifting using a panel econometric model, and he found evidence for complete forward shifting and even *over*shifting, where prices rose more than the cost of the tax [38]. Another study conducted in Maryland similarly found that even though assuming complete forward shifting overstates the overall regressivity of the sales tax by failing to consider the effect of business-to-business transactions, the forward-shifting assumption does accurately reflect the incidence among consumers [36]. As a result, we undertake this analysis using the assumption of forward shifting.

## METHODOLOGICAL APPROACH

How much do different people pay under sales taxes versus how much they would pay under congestion/value pricing? This is a central, but surprisingly unexamined, question in transportation finance. To find the answer we examine California's State Route 91 (SR91) HOT lanes project. The priced section California's SR91 is constructed in the median of a 10-mile stretch of the congested freeway that links job-rich locations in Orange County in the southeastern part of metropolitan Los Angeles, with the housing-rich "Inland Empire" in western San Bernardino and Riverside Counties to the northeast. The lanes operate with completely automated toll collection using transponders and roadside sensors. The California Private Transportation Company originally owned and operated the toll lanes under a 35-year contract. The company agreed to cap returns on the facility to 17 percent, but could otherwise set its own tolls. The project opened December 27, 1995. In 2002, the Orange County Transportation Authority, the public operator of transit service in Orange County, negotiated to the buy the facility; since January 2003, the facility has operated under public oversight. The revenues generated by SR91 in 2003 were $34.7 million USD and $39 million USD in 2004-2005 [39]. We use $34 million as a revenue requirement to be raised either by tolls or by sales taxes, in order to better match the SR91 usage data survey data from 1999 and the Consumer Expenditure Survey data from 2002.

While the SR91 project was finance with revenue bonds that are being retired with value-priced toll revenues, we consider a second, and more common in the U.S., option for financing the of the SR91 facility: a local option transportation sales tax. The base sales tax rate in California (as of 1 June 2004) is 7.25%; of that, 1 percent of the levy is dedicated to counties and cities for transportation and other local infrastructure needs. In addition to the base rate, the voters of Orange County in southern California, where the SR91 project is located, approved Measure M in 1990, which added a half-cent to the sales tax specifically earmarked for transportation, bringing the local sales tax rate to 7.75%. We thus ask the hypothetical: what if $34 million in revenues from SR91 tolls had been built with Measure M revenues rather than by value pricing revenues?

Consumer expenditure models estimate the cost burden associated general taxable consumption, and are used to test the effects of Orange County's Measure M. To measure the total expenditures under each different policy, the costs are summed to estimate the cost burden on representative consumers at each income level. For the sales tax, the consumer expenditure model is estimated using the Bureau of Labor Statistics Consumer Expenditure Survey (CES) data for 2002. The CES has two major components: a) an interview panel survey for which 5,000 households report on expenditures every three months and b) a follow-up of the same sample size in which households keep an expenditure diary for two consecutive weeks. The data used in this paper are a subset of the 2002 CES data in that the data do not include households that did not report incomes or participate in both weeks of the diary survey; in sum, the complete sample contained 4,318 respondents from around the U.S..

In order to calculate taxable expenditures, one must exclude from total expenditures those not subject to the sales tax. To help mitigate the inherent income regressivity of sales taxes, California, like many states, exempts basic necessities like groceries, medicine, and so on from the sales tax. Our variable of taxable expenditures $T_i$ is constructed by applying a factor of 1 to all expenditures *(X)* in taxable categories (*k*) reported in the Consumer Expenditure Survey and 0 to all nontaxable expenditure categories:

$$\mathbf{T} = \begin{bmatrix} X_1^1 & \cdots & X_1^k \\ \vdots & \ddots & \vdots \\ X_i^1 & \cdots & X_i^k \end{bmatrix} \times \mathrm{t}$$

$$\text{where t=}\begin{cases} 0, \text{ if } k \text{ is taxable} \\ 1, \text{ if } k \text{ is nontaxable} \end{cases}$$

The total taxable expenditure for each consumer is then summed across categories, creating $T_i = \sum_1^k X_i$ as the dependent variable in the expenditure models.

**Expenditure models**

The representation of consumer expenditures—whether on tollway trips or on food—is traditionally guided by Engel's law; as income increases, the proportions spent on any given items change. For example, as incomes increase, the proportion spent on basic needs such as food decrease (because the total amount of food consumed does not increase proportionally as incomes rise) while the portion spent on discretionary items, such as cars, electronics, vacations, boats, etc., increases – thus the functional form of the representation should be nonlinear. Given that most sales taxes, like the one in California, are structured to minimize taxing essential expenses, many expenditures subject to tax are not universally consumed, either due to preferences (such as bicyclists who do not purchase gasoline), item durability, or other issues related to context. The zero value in this context is important; some SR91 users simply may not use the facility, just as some consumers may not purchase any clothing, during a given time period. For this reason, the "double hurdle" models of consumer expenditure reflect first the probability of purchase, and then how much to purchase. Together, the two stages predict the level of expenditure for a representative consumer. The models reported on in this manuscript follow the work of Cragg [40], adapted slightly. The probability of goods purchase ( $P_j$ ) is estimated using the familiar logit form, while a separate model of expenditure levels, *E (T)*, is estimated using OLS regression.

The results of the logit purchase probability model are shown in the first column of Table 1. The second column of Table 1 displays the results of the second expenditure level regression model, which tests the same set of explanatory variables as the logit. Even though the OLS model shows a comparatively low overall fit with an adjusted R-square of 0.1932, the model is significant, and the variables demonstrate the expected signs, relative magnitudes, and significance levels for those we expect influence taxable expenditures. As expected, income is strong and positively related to expenditures; the more people make, the more they spend on both taxable and nontaxable goods. Regional dummy variables show that those reporting from the Western U.S. have higher taxable expenditures than either the Midwest or the Northeast, though those all are higher than the base region of the South.

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As expected, a dummy variable for mortgage-holding homeowners demonstrates a strong, positive relationship with taxable expenditures, which is likely related to income. However homeowners would also be expected to incur higher expenses related to home maintenance and home improvements, which tend to be taxable expenses. Homeowners without mortgages, who are more likely to be older homeowners, are the base case here. Renters pay less in taxable expenses than either of the owner categories.

**[Table 1. Consumer Expenditure Models]**

Being single tends to decrease the amount of taxable outlays, although not uniformly. An interaction term between dummies for single motherhood and fatherhood show that neither of those significantly affect the likelihood of purchase, but single motherhood does decrease the amount of taxable expenditure. However, an interaction term between the dummy variable denoting single motherhood and income shows a strong, positive association, so that as incomes get higher among single mothers, they are more likely than other groups to consume taxable goods and services. This would make sense, as many taxable services, like food consumed away from home, are useful time savers for a single parent.

The findings with regard to race and ethnicity are mixed, though are a few consistent findings that merit attention. Latino and Asian respondents consistently spend less on taxable goods then either their white (the base case) or their African American counterparts. This is true even when interacted against income, suggesting that, even at higher income levels, Latino and Asian groups spend less on taxable goods than whites. The coefficients are similar for African Americans households, but the estimates are not significant.

Finally, family status does not appear to affect the probability that a household will make taxable expenditures, but the number of children in a household and their ages do. The more children, the higher the taxable and total outlays a household makes. Also, families with older children (over the age of 15) spent significantly more on taxable items than do those who have young children (under 2). Families with children aged 2 to 15 also spend more than those with young

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children. As expected, households with at least one retired person spend significantly less on taxable goods.

The OLS regression findings demonstrate that, in constructing representative consumers in Orange County, there are good reasons to differentiate by income level, gender, ethnicity, family type, and parental status. However, it becomes too cumbersome to stratify by all these variables, as well as number and ages of children. Thus, bases on the results observed here, we stratify by family type (which includes gender of householder) and income. It is important to distinguish consumer expenditure units by gender, especially, because a disproportionate number of women head households in the lower income deciles. Although incomes in Orange County, CA are higher than the U.S. on average (and higher than most of California), there are large working class and lower-income neighborhoods as well. The concentration of women in lower income households is shown in Figure 1.

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**[Figure 1. Distribution of income (quintiles) by household type, Orange County]**

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To estimate the total outlay of taxable expenditure by household category, the predicted probability of purchase estimated in the first stage is multiplied by the OLS estimate to derive an average predicted expenditure $E[T]$, which is weighted by $P_j$, the probability of purchase. Thus Table 2 shows the expected expenditure for each stratum, the yearly tax that results from a half-cent sales tax, and, in the last column, the percentage of the median income. For each household type, the percentage of income spent on taxable expenditures is inversely related to income,

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demonstrating that a one-half cent sales tax is indeed regressive, even though total sales tax payments increase with income.

**[Table 2. Predicted Taxable Expenditures]**

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The best predictor of taxable expenditures is total expenditures, rather than income. There are a number of reasons for this. For one, reporting in the CES is lower for income than total expenditures. Median expenditures at the lowest income decile are comparable to those in the second and third deciles, even though the income levels are not. Households reporting zero income can occur for several reasons. Retirees who may be quite wealthy in terms of assets may report very little income from traditional sources, but substantial expenditures. Second, income reporting may in general be less accurate than out-of-pocket expenditures. Third, low-income families may be reluctant to report income they received from informal work or gifts for fear that it may affect their eligibility for various public income support programs. Fourth, lower income households are more likely to be involved in seasonal work, like construction or agriculture, that brings in quite a bit of money during part of the year and almost none the rest. Finally, low-wage workers frequently move into and out of paid work, increasing the probability of going through a period of unemployment with expenditures, but little or no income. For all these reasons, expenditures have proven a better proxy for income available for expenditures than self-reported after-tax income, especially for lower-income households. Unfortunately, the U.S. Census reports incomes and not expenditures, so in order to apply the results of the expenditure models to Orange County residents, we are limited to the admittedly imperfect income data rather than the likely more accurate expenditure data. But because income performs so poorly in models for the 1st income decile, we treat the median reported expenditure as the expected expenditures just for this income group rather than using the model estimates.

**ORANGE COUNTY SALES TAXES AND TOLLS**

In order to approximate the total contributions to sales taxes by Orange County residents, the expected taxable expenditures, $E[T]$, for each representative consumer are assumed to apply to each family type $f$ in each income group $d$ in Orange County. The expected expenditure is multiplied by the number $N$ of families in each family type $f$ in each income group $d$:

$$\overline{\mathbf{T}} = \begin{bmatrix} E[T]_1^1 \\ \vdots \\ E[T]_{10}^f \end{bmatrix} \times \begin{bmatrix} N_1^1 & \cdots & N_d^f \end{bmatrix}$$

Each individual element in the resulting matrix $\overline{\mathbf{T}}$ is the total contribution of any one family type in any income group. The total tax contribution of any income decile is simply summed across all family types, or $\sum_1^f T_d$, and summed across all income groups for a total tax revenue prediction. When checked against the total taxable sales of Orange County, which run to just under $45 billion USD [41, Table 2]; the total Measure M revenue from that should be $240 million. A sizable portion of this will be paid by non-residents of Orange County, which home to Disneyland, beaches, and major retail, sports, and entertainment centers, which combined attracted nearly 25.3 million visitors in 2003 who added $161 million USD to the county's local sales tax receipts [42, p. 63]. Business transactions, too, contribute to the total sales tax take. Thus, our model predicts the Orange County household sector's share of total sales tax receipts at a little less than half of total sales tax receipts, with travelers, external residents, and businesses making up the rest.

Because there is a sample of revealed toll payment behavior from the SR91 facility, it is not necessary to construct expected toll revenues. Instead, data from the most recent survey of SR91 users (and nonusers) collected in the fall of 1999 supplies basic information about toll use and timing by basic household characteristics, such as income and the presence of children in the household. However, the survey did not ask about ethnicity data or separate out single from other parents. If we assume that the sample of 1,788 respondents are representative of all facility users and nonusers, we can treat each income group's relative contribution to the total take derived from the users in the sample to total SR91 revenue of $34 million USD. However, the sample data from SR91 asked for income not by decile or quintile, but in six categories, so that these must be sorted into quintiles. To match the SR91 data, the calculated sales tax data are also sorted into quintiles as well.

The resulting distributions of revenues under the two schemas, the voluntary toll payments by users of the SR91 facility and the involuntary payments of sales taxes, are shown in Table 3. According to this income quintile analysis, households in the lowest quintile contribute a negligible amount to SR91 toll revenue, because the sample shows that this group seldom uses the facility, and when they do, they are more likely than those in higher income categories to pay during less congested, lower-toll-rate time periods. As a group, however, they contribute over $3 million USD under a sales tax regime. Their contribution, along with a contribution of over $4 million from the highest quintile, is redistributed to the middle deciles, who fare much better under a general tax than under a tolling scheme, because they are the heaviest users of the facility.

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[Table 3. Estimated Contributions to SR91 Costs by Income Quintile]

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**HOUSEHOLD-LEVEL PRICE INCENTIVES**

In addition to examining the relative transfer of toll and sales tax payments among lower to higher income groups under the two pricing schemes, it is also important to examine how the different instruments affect the price and incentive structure for representative consumers. To do so, we have constructed 140 different representative consumers based on income deciles and SR91 usage. Table 4 lays out the SR91 usage profiles for heavy, moderate, and infrequent users of the facility whose usage occurs during peak and nonpeak hours. We assume that those who travel during the peak hours do so because they cannot avoid it. Heavy, peak usage is also analogous to a congestion charge.

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[Table 4. Estimated Annual SR91 Costs for Representative Sample of Users]

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The 120 representative consumers are single mother families and married couple families from each income decile that fall into each of the usage profiles. The amount of savings that a family of SR91 users would derive if the facility had been provided via a sales tax is the simply the total yearly toll less the yearly sales tax paid (from Table 2). We assume that the travel benefits are equal or greater than the tolls paid; otherwise, the driver would not pay them. We further assume that facility operates in uncongested conditions, at least for a time, even with the sales tax financing rather than the toll, because of the increased capacity, and that the unpriced conditions lead to congestion only after some time has elapsed. While we have excluded from this analysis consideration of how the two financing approaches would likely effect longer-term

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levels of delay, fuel consumption, and emissions from this analysis, there is a large theoretical and more recent empirical literature to suggest that congestion/value pricing, like on SR91, is likely to reduce delay, fuel consumption, and emissions vis-à-vis sales tax finance of the facility.

The results for individual representative households are shown in Table 5, which shows why so many worry about the effects of a congestion charge on lower income travelers. Just as the sales tax burden is regressive with respect to income, the benefits from *not paying* for uncongested road service are progressively distributed, but this is only true among drivers use the facility. Because the lowest income groups seldom use the facility, their benefits are negligible. However, by the third decile, frequent users of the facility, as individual consumer expenditure units, benefit substantially from shifting the costs of the facility onto the residents, businesses, and travelers in Orange County via the sales tax. For nonusers and some groups of infrequent users, the costs of the sales taxes are substantially higher than what they currently pay in tolls—the magnitude of the cost burden under a sales tax is much smaller than the potential costs associated with a toll. The out-of-pocket gain from voting for a sales tax rather than a toll would provide a savings of up to $700 a year for heavy users in lower income groups—a sizable cost savings to those who would need the facility frequently during peak times.

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**CONCLUSIONS**

The estimates developed for this analysis illustrate the trade-offs involved in turning to general sales taxes as a means to finance infrastructure, rather user charges. The sales tax, because it is paid by virtually every one, spreads the costs of infrastructure across a broad base of consumers. It costs each family comparatively little, but the contributions are regressively distributed. Poor households sacrifice proportionally more of their resources than do more affluent households, and, as a group the lowest quintile would contribute over $3 million a year if the revenues from the SR91 were to come from sales taxes rather than tolls.

The regressivity of the sales tax is an issue by itself, but it becomes even more a concern when we see how much sales taxes, when spent of transportation projects that benefit individual users of an improved facility, redistribute cost burdens from users to non-users. In this case, the heaviest users of SR91 – and thus the largest beneficiaries of the time savings it provides and those who pay the most for the facility through tolls – are from middle- and upper-middle income households . If Measure M had financed the SR91 facility, it would lower the costs of driving on SR91 significantly. From a regional planning perspective, providing freeway capacity using the sales tax is, in effect a pro-driving policy that taxes all residents to provide individual benefits to a sub-set of drivers and their passengers. While not all of these drivers are well-to-do, such as those in the comparatively nonaffluent $3^{rd}$ decile income group, the overall effect of sales tax finance would be to transfer resources from lower-income households to those with higher incomes via the sales taxes. This is especially the case given the possibilities that the environmental, energy, safety, and congestion externalities associated with driving may also be regressively distributed [43]. If these externalities are, in fact, regressively distributed, then the sales tax effectively taxes poorer residents to support an activity whose side effects harm them.

Although regressive, sales taxes are easy to understand and collect; furthermore, families, even if they pay more than they would under a tolling scheme, can spread the costs of sales taxes throughout the entire year and pay a little at a time, at point of purchase, rather than having to come up with larger cash payments less frequently (as they must for vehicle registration or buying a transponder). Again, however, the sales tax's invisibility and ease, and its disassociation from driving, changes the relative prices of trips (and everything else) such that individuals have no price signals to follow when making housing or travel choices. As a matter of policy, we cannot expect individual drivers to make pro-social or pro-environmental decisions about their driving behavior if such costs are hidden to this extent, and if financing methods are designed to shield them from even perceiving the costs their travel imposes on society.

Finally, the problems with the sales tax we have outlined here should not be generalized to sales taxes that provide transit-related infrastructure rather than freeway expansion. If the transit provided via the sales tax were targeted towards services for existing transit riders especially, the sales tax could in theory transfer resources towards more impoverished income groups. As others have shown, toll revenues spent on transit can help make their ultimate effect less regressive and, in some cases, progressive [26], and the same may be true of sales taxes. The decision to pursue sales taxes in order to provide roadways creates substantial incentives to drive and systematically favors the more affluent at the expense of the impoverished. If the future of our cities depends on the infrastructure choices we make, these, too, depend on the financing decisions we simultaneously take, and both portend substantial consequences for both equity and environment.

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**REFERENCES**

1. Brown, J., *Race, class, gender, and public transportation* Critical Planning Journal 1998. **Spring** p. 3-20.

2. Harvey, G. *Transportation and travel behavior*, in *Curbing Gridlock*. 1992, Transportation Research Board: Washington, DC. p. 89-119.

3. Giuliano, G., *Equity and fairness considerations of congestion pricing*, in *Curbing Gridlock* 1994, Transportation Research Board, National Academy Press Washington, DC p. 250-279.

4. Sorenson, P. and B. Taylor, *Review and synthesis of road-use metering and charging systems*, t.N.A. Transportation Research Board, Editor. 2005.

5. Small, K., *Urban Transportation Economics* 1992, New York Harwood Academic Publishers

6. Vickrey, W.S., *Marginal cost pricing* in *Public Economics: Selected Papers by William* R. Arnott, Editor. 1994, Cambridge University Press: Cambridge p. 198-215.

7. Dill, J., T. Goldstein, and M. Wachs, *California vehicles fees: Incidence and equity* Journal of Transportation and Statistics 1999. **2**(2): p. 133-148.

8. Goldstein, T., S. Corbett, and M. Wachs, *Local Option Transportation Taxes in the United States: Issues and Trends.* . 2001: Berkeley, CA

9. Brown, J., *Reconsidering the Gas Tax: Paying for What You Get.* Access 2001. **19**: p. 10-15.

10. Taylor, B., *Public perceptions, fiscal realities, and freeway planning: The California case* Journal of the American Planning Association, 1995. **61**(1): p. 43-56.

11. Cohen, Y., *Commuter welfare under peak-period congestion tolls: Who gains and who loses?* . International Journal of Transport Economics 1987. **14**(3): p. 239-266.

12. Richardson, H. and C. Bae, *The equity impacts of road pricing* in *Road pricing, traffic congestion, andthe environment: Issues of efficiency and social equity* E. Verhoef and K. Button, Editors. 1998, Edward Elgar London. p. 247-262.

13. Arnott, R., A. de Palma, and R. Lindsey, *The welfare effects of congestion tolls with heterogeneous commuters* Journal Transport Economics and Policy 1994. **28**(May ): p. 139-161.

14. Glazer, A. and E. Niskanen, *Which consumers benefit from congestion tolls?* . Journal of Transport Economics and Policy 2000. **34**(January ): p. 43-54.

15. Harvey, G.W., *Transportation pricing and travel behavior*, in *Curbing Gridlock*. 1992, Transportation Research Board: Washington, DC. p. 89-119.

16. Kalmanje, S. and K.M. Kockelman, *Credit-based congestion pricing: Travel, land value and welfare impacts* Transportation Research Record 2004. **1864**: p. 45-53.

17. Santos, G., *Preliminary results of the London congestion charging scheme.* Public Works Management & Policy 2004. **9**(2): p. 164-181.

18. Santos, G. and L. Roley, *Distributional impacts of road pricing: The truth behind the myth.* Transportation 2004. **31**: p. 21-42.

19. Yang, H. and X. Zhang, *Multi-class toll design problem with social and spatial equity constraints* Journal of Transportation Engineering 2002. **128**(5): p. 420-428.

20. Bates, J., et al., *The value of reliability for personal travel* Transportation Research Part E, 2001. **37**(2-3): p. 191-229.

21. Mokhtarian, P. and E. Raney, *Behavioral response to congestion: Identifying patterns and socio-economics differences in adoption.* Transport Policy 1997. **4**(3): p. 147-160.

22. Mastako, K., L.R. Rilett, and Sullivan, *Commuter behavior on California State Route 91--After introducing variable-toll express lanes* Transportation Research Record 1617, 1998: p. 163-170.

23. Sullivan, E., *State route 91 value-priced express lanes: updated observations* Transportation Research Record 2002. **1812**: p. 37-42.

24. Sullivan, E. and J. El Harake, Transportation Research Board Record 1649, 1998.

25. Parkany, E., *Can HOT lanes encourage carpooling? A case study of carpolling behavior on the 91 express lanes.* . Transportation Research Board Record 1682, 1999: p. 46-54.

26. Small, K.A., *Unnoticed lessons from London: Road pricing and public transit* Access, 2004. **26**: p. 10-15.

27. Fullerton, D. and D.L. Rogers, *Who Bears the Lifetime Tax Burden* 1993, The Brookings Institution: Washington, DC.

28. Baum, D.N., *Economic effects of including services in the sales tax base: An applied general equilibrium analysis.* Public Finance Quarterly, 1991. **19**(2): p. 166-192.

29. Gentry, W.M. and H.F. Ladd, *State tax structure and multiple policy objectives* National Tax Journal, 1994. **47**(4): p. 747-769.

30. Santi, L., *Estimates of the state sales and use tax on Arkansas households, 1989-1995.* Arkansas business and economic review 1994. **27**(1): p. 10-18.

31. Taylor, B., *The Geography of Transportation Finance* in *The Geography of Urban Transportation* S. Hanson and G. Giuliano, Editors. 2004, The Guilford Press New York. p. 294-331.

32. Wachs, M., *A dozen reasons for raising gasoline taxes*, U.o.C.a.B. Institute of Transportation Studies, Editor. 2003.

33. Forkenbrock, D. and J. Kuhl, *A new approach to assessing road user charges*, U.o.I.P.P. Center, Editor. 2002, University of Iowa Public Policy Center: Iowa City, IA

34. Council, O.C.B., *Measure M Assessment 1990-2005*. 2006, Orange County Business Council Irvine, CA

35. Due, J.F. and J.C. Mikesell, *Sales Taxation*. 1994, Washington, DC: Urban Institute

36. Derrick, F.W. and C.E. Scott, *Sales tax equity: Who bears the burden?* The Quarterly Review of Economics and Finance 1998. **38**(2): p. 227-237.

37. Besley, T.J. and H. Rosen, *Vertical externalities in tax setting: Evidence from gasoline and cigarettes* Journal of Public Economics 1998. **70**: p. 383-398.

38. Poterba, J., *Retail price reactions to changes in state and local sales taxes.* National Tax Journal 1996. **27**(Fall): p. 169-179.

39. Authority, O.C.T., *91 Express Lanes Fast Facts* nd.

40. Cragg, J.G., *Some statistical models for limited dependent variables with application to the demand for the durable goods.* Econometrica, 1971: p. 829-844.

41. Equalization, C.S.B.o. *Taxable Sales in California* 2005 [cited 2006 June 20, 2006].

42. Associates, D.R., *California Travel Impacts by County* 2006, California Tourism Sacramento

43. Schweitzer, L. and A. Valenzuela Jr, *Environmental Justice and Transportation: The Claims and the Evidence.* Journal of Planning Literature, 2004. **18**(4): p. 383-398.

**Table 1. Consumer Expenditure Models**

| | Logit $P_j$ | | | Taxable expenditures | |
|---|---|---|---|---|---|
| | **Beta** | **Std. Error** | | **Beta** | **Std. Error** |
| Intercept | 3.455*** | 0.1481 | | 1556*** | 79.4 |
| After tax income | 0.0004586*** | 0.0000396 | | 0.002917*** | 0.00634 |
| Small city | -0.029050* | 0.0117 | | -367.7 003212*** | 66.99 |
| Western region | 1.115*** | 0.1670 | | 532.4*** | 69.11 |
| Northeast region | 0.478** | 0.07799 | | 406.1*** | 77.89 |
| Midwest region | 0.8091*** | 0.1455 | | 358.02*** | 69.43 |
| Homeowner with mortgage dummy | 0.908*** | 0.1819 | | 371.5*** | 71.5 |
| Renter dummy | -0.2193$^{\varphi}$ | 0.1266 | | -542.60*** | 74.22 |
| Children | 0.009164 | 0.08106 | | 154.7*** | 32.88 |
| Retirement age | 0.3908*** | -0.08057 | | -377.02*** | 45.9 |
| African American | 0.0172*** | 0.04040 | | -374.2 | 354.3 |
| Latino | -0.7285*** | 0.1750 | | -372.22** | 121.5 |
| Asian | 0.1130 | 0.3941 | | -201.8 | 173.7 |
| Single mother | -0.4568 | 0.3857 | | -688.03*** | 207.6 |
| Single father | 0.1717 | 0.2075 | | 525.1 | 579.2 |
| Children 2-15 | -0.7318** | 0.2796 | | 279.9** | 101.4 |
| Children over 15 | 0.6329 | 0.3879 | | 364.2*** | 102.4 |
| Income*Asian | -0.2673* | 0.00012 | | -6188.04** | 2515.3 |
| Inc*African American | 0.00006088 | 0.00003795 | | -9885.06 | 6748.3 |
| Inc*Latino | 0.00001435 | 0.0000194 | | -6960.30** | 2515.97 |

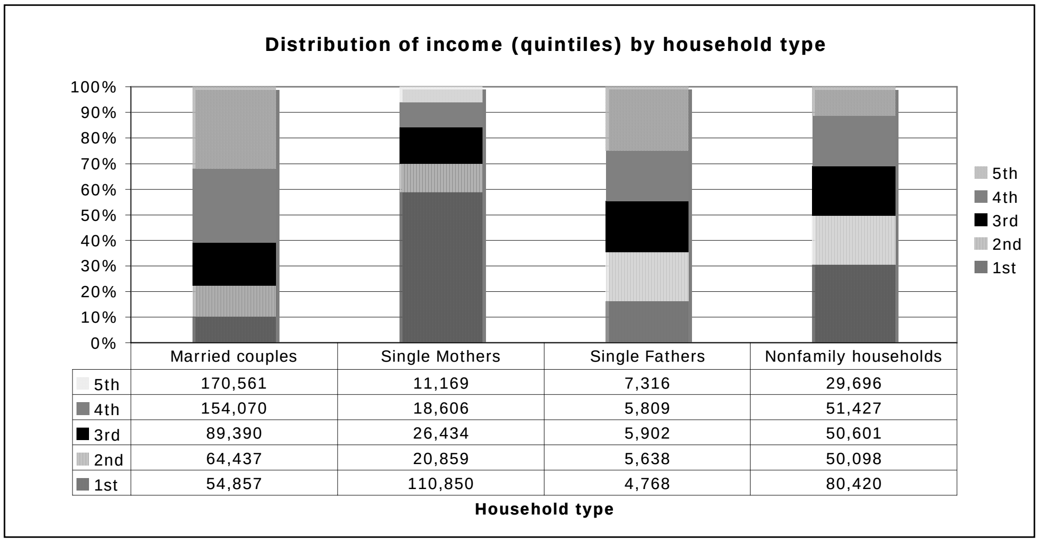
SOURCE: Consumer Expenditure Survey, model results by the authors

Table 2. Predicted Taxable Expenditures

Deleted: 3

| | Family households | | | | Nonfamily households | | | |
|---|---|---|---|---|---|---|---|---|
| **Decile** | **Median income** | $E[T]$ | **Tax** | **Percent of income** | **Median income** | $E[T]$ | **Tax** | **Percent of income** |
| **Single women** | | | | | | | | |
| 1 | $0 | $2,764 | $13.82 | | $648 | $1,708 | $17.08 | 2.64% |
| 2 | 7,595 | 3,088 | 15.44 | 0.20% | 7,536 | 1,228 | 12.28 | 0.16 |
| 3 | 12,500 | 3,708 | 18.54 | 0.15 | 12,310 | 2,014 | 20.15 | 0.16 |
| 4 | 17,000 | 4,064 | 20.32 | 0.12 | 17,388 | 3,088 | 30.88 | 0.18 |
| 5 | 24,600 | 4,856 | 24.28 | 0.10 | 24,000 | 4,212 | 42.12 | 0.18 |
| 6 | 34,000 | 6,576 | 32.88 | 0.10 | 34,100 | 6,636 | 66.36 | 0.19 |
| 7 | 43,932 | 8,676 | 43.38 | 0.10 | 44,158 | 7,116 | 71.16 | 0.16 |
| 8 | 56,000 | 9,132 | 45.66 | 0.08 | 58,000 | 9,272 | 92.72 | 0.16 |
| 9 | 79,888 | 9,580 | 47.9 | 0.06 | 81,779 | 10,728 | 107.28 | 0.13 |
| 10 | 113,669 | 16,648 | 83.24 | 0.07 | 128,285 | 16,340 | 163.4 | 0.13 |
| **Single men** | | | | | | | | |
| 1 | 0 | 4,332 | 43.32 | | 540 | 2,508 | 25.08 | 4.64 |
| 2 | 7,968 | 4,024 | 40.24 | 0.51 | 7,300 | 1,720 | 17.2 | 0.24 |
| 3 | 12,000 | 5,600 | 56 | 0.47 | 12,060 | 2,440 | 24.4 | 0.20 |
| 4 | 17,540 | 3,648 | 36.48 | 0.21 | 17,000 | 3,080 | 30.8 | 0.18 |
| 5 | 24,000 | 4,428 | 44.28 | 0.18 | 24,555 | 3,602 | 36.028 | 0.15 |
| 6 | 34,668 | 5,672 | 56.72 | 0.16 | 34,056 | 5,356 | 53.56 | 0.16 |
| 7 | 43,833 | 6,052 | 60.52 | 0.14 | 44,420 | 7,328 | 73.28 | 0.16 |
| 8 | 58,928 | 9,344 | 93.44 | 0.16 | 59,000 | 9,532 | 95.32 | 0.16 |
| 9 | 78,000 | 10,120 | 101.2 | 0.13 | 81,394 | 11,712 | 117.12 | 0.14 |
| 10 | 115,080 | 10,604 | 106.04 | 0.09 | 130,000 | 15,888 | 158.88 | 0.12 |
| **Married couple** | | | | | | | | |
| 1 | 0 | 5,380 | 53.8 | | 0 | 4,404 | 44.04 | |
| 2 | 7,896 | 4,580 | 45.8 | 0.58 | 7,900 | 3,832 | 38.32 | 0.49 |
| 3 | 12,948 | 3,432 | 34.32 | 0.27 | 13,015 | 2,847 | 28.47 | 0.22 |
| 4 | 17,462 | 3,408 | 34.08 | 0.20 | 17,838 | 2,956 | 29.56 | 0.17 |
| 5 | 24,500 | 4,716 | 47.16 | 0.19 | 24,211 | 4,260 | 42.6 | 0.18 |
| 6 | 35,000 | 6,100 | 61.00 | 0.17 | 34,736 | 6,110 | 61.00 | 0.18 |
| 7 | 44,567 | 7,724 | 77.24 | 0.17 | 44,833 | 11,896 | 118.96 | 0.27 |
| 8 | 59,066 | 9,824 | 98.24 | 0.17 | 54,850 | 11,840 | 118.4 | 0.22 |
| 9 | 82,000 | 11,840 | 118.4 | 0.14 | 82,714 | 16,460 | 164.6 | 0.20 |
| 10 | 129,300 | 16,460 | 164.6 | 0.13 | 13,1300 | 22,572 | 225.72 | 0.17 |

**SOURCE:** data compiled by the authors




| | Married couples | Single Mothers | Single Fathers | Nonfamily households |
|---|---|---|---|---|
| 5th | 170,561 | 11,169 | 7,316 | 29,696 |
| 4th | 154,070 | 18,606 | 5,809 | 51,427 |
| 3rd | 89,390 | 26,434 | 5,902 | 50,601 |
| 2nd | 64,437 | 20,859 | 5,638 | 50,098 |
| 1st | 54,857 | 110,850 | 4,768 | 80,420 |

**Figure 1. Distribution of income (quintiles) by household type, Orange County**

**SOURCE:** Data compiled by the authors from the US Census, STF File 3.

**Table 3. Estimated Contributions to SR91 Costs by Income Quintile Under Two Finance Methods**

Deleted: 5

| Quintile | Sales taxes | Tolls | Profit/loss |
|---|---|---|---|
| 1st | $3,353,241 | $0.00 | –$3,353,242 |
| 2nd | 1,789,375 | 3,906,577 | 2,117,202 |
| 3rd | 3,977,632 | 7,345,369 | 3,367,737 |
| 4th | 10,798,820 | 12,731,744 | 1,932,924 |
| 5th | 14,080,930 | 10,006,040 | –4,074,890 |

SOURCE: Data compiled by the authors

**Table 4. Estimated Annual SR91 Costs for Representative Sample of Users**

Deleted: 7

| | Peak period | | | Off-peak user | | |
|---|---|---|---|---|---|---|
| | **Heavy** | **Moderate** | **Infrequent** | **Heavy** | **Moderate** | **Infrequent** |
| Toll | $3.6 | $3.6 | $3.6 | $1.65 | $1.65 | $1.65 |
| Times per week | 5 | 3 | 1 | 5 | 3 | 1 |
| Number of weeks | 40 | 30 | 20 | 45 | 35 | 20 |
| Yearly cost | $720 | $324 | $72 | $371.25 | $173.25 | $33 |

SOURCE: Toll levels from SR91 documentation, other numbers are the authors' assumptions and calculations

**Table 5. Driver Savings from Sales Taxes (Representative Consumers)**

Deleted: 9

| | Peak period | | | | | | Off-peak user | | | | | | Nonusers | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Heavy | | Moderate | | Infrequent | | Heavy | | Moderate | | Infrequent | | | |
| **Single women** | | | | | | | | | | | | | | |
| 1 | $0.00 | 0.00% | $0.00 | 0.00% | 0.00 | 0.00% | $0.00 | 0.00% | $0.00 | 0.00% | $0.00 | 0.00% | -$13.82 | 0.00% |
| 2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -46.88 | -0.62 |
| 3 | 701.46 | 5.61 | 305.46 | 2.44 | 53.46 | 0.43 | 352.71 | 2.82 | 154.71 | 1.24 | 14.46 | 0.12 | -18.54 | -0.15 |
| 4 | 699.68 | 4.12 | 303.68 | 1.79 | 51.68 | 0.30 | 350.93 | 2.06 | 152.93 | 0.90 | 12.68 | 0.07 | -20.32 | -0.12 |
| 5 | 695.72 | 2.83 | 299.72 | 1.22 | 47.72 | 0.19 | 346.97 | 1.41 | 148.97 | 0.61 | 8.72 | 0.04 | -24.28 | -0.10 |
| 6 | 687.12 | 2.02 | 291.12 | 0.86 | 39.12 | 0.12 | 338.37 | 1.00 | 140.37 | 0.41 | 0.12 | 0.00 | -32.88 | -0.10 |
| 7 | 676.62 | 1.54 | 280.62 | 0.64 | 28.62 | 0.07 | 327.87 | 0.75 | 129.87 | 0.30 | -10.38 | -0.02 | -43.38 | -0.10 |
| 8 | 674.34 | 1.20 | 278.34 | 0.50 | 26.34 | 0.05 | 325.59 | 0.58 | 127.59 | 0.23 | -12.66 | -0.02 | -45.66 | -0.08 |
| 9 | 672.1 | 0.84 | 276.1 | 0.35 | 24.1 | 0.03 | 323.35 | 0.40 | 125.35 | 0.16 | -14.9 | -0.02 | -47.9 | -0.06 |
| 10 | 636.76 | 0.56 | 240.76 | 0.21 | -11.24 | -0.01 | 288.01 | 0.25 | 90.01 | 0.08 | -50.24 | -0.04 | -83.24 | -0.07 |
| **Married couple** | | | | | | | | | | | | | | |
| 1 | $0.00 | 0.00% | $0.00 | 0.00% | 0.00 | 0.00% | $0.00 | 0.00% | $0.00 | 0.00% | $0.00 | 0.00% | -26.9 | 0.00 |
| 2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -22.9 | -0.29 |
| 3 | 702.84 | 5.43 | 306.84 | 2.37 | 54.84 | 0.42 | 354.09 | 2.73 | 156.09 | 1.21 | 15.84 | 0.12 | -17.16 | -0.13 |
| 4 | 702.96 | 4.03 | 306.96 | 1.76 | 54.96 | 0.31 | 354.21 | 2.03 | 156.21 | 0.89 | 15.96 | 0.09 | -17.04 | -0.10 |
| 5 | 696.42 | 2.84 | 300.42 | 1.23 | 48.42 | 0.20 | 347.67 | 1.42 | 149.67 | 0.61 | 9.42 | 0.04 | -23.58 | -0.10 |
| 6 | 689.5 | 1.97 | 293.5 | 0.84 | 41.5 | 0.12 | 340.75 | 0.97 | 142.75 | 0.41 | 2.5 | 0.01 | -30.5 | -0.09 |
| 7 | 681.38 | 1.53 | 285.38 | 0.64 | 33.38 | 0.07 | 332.63 | 0.75 | 134.63 | 0.30 | -5.62 | -0.01 | -38.62 | -0.09 |
| 8 | 670.88 | 1.14 | 274.88 | 0.47 | 22.88 | 0.04 | 322.13 | 0.55 | 124.13 | 0.21 | -16.12 | -0.03 | -49.12 | -0.08 |
| 9 | 660.8 | 0.81 | 264.8 | 0.32 | 12.8 | 0.02 | 312.05 | 0.38 | 114.05 | 0.14 | -26.2 | -0.03 | -59.2 | -0.07 |
| 10 | 637.7 | 0.49 | 241.7 | 0.19 | -10.3 | -0.01 | 288.95 | 0.22 | 90.95 | 0.07 | -49.3 | -0.04 | -82.3 | -0.06 |

SOURCE: Data imputed by the autho

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