Pigou Creates Losers: On the Implausibility of Achieving Pareto Improvements from Pigouvian Taxation

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Abstract

A Pigouvian tax imposes initial burdens by raising prices, but it generates revenue plus efficiency gains that are greater than the sum of these burdens. This paper uses theory and data to ask when those gains can be reallocated so as to achieve a Pareto improvement. I derive a necessary condition for a Pigouvian tax to create a Pareto improvement that can be tested directly with data. The condition relates the size of efficiency gains to the degree of predictability between initial burdens and variables used to determine a transfer scheme. This makes clear that compensating losers so as to achieve a Pareto improvement is fundamentally a prediction problem. The main empirical application is to a gasoline tax to correct carbon emissions, though related results are presented for other sin taxes. Results indicate that it is infeasible to create a Pareto improvement from the taxation of these goods, and moreover that plausible policies are likely to leave a large fraction of households as net losers.

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1 Introduction

Why do efficient policies so often fail to gain political traction? Efficient policies, like a carbon tax, are frequently eschewed in favor of higher cost regulatory alternatives or even inaction. There are numerous possible explanations, but a common argument regards the distribution of welfare burdens imposed by the policy. There are two varieties of this argument. In one, a policy is disliked because it is regressive and disproportionately affects low-income households. In the other case, a policy imposes a substantial burden on a particular firm, set of firms, or group of voters who mobilize to block the policy.

In either case, economic theory provides a potential reply, which is that such losers can be compensated. Any efficiency-enhancing policy, by definition, creates enough new surplus to compensate all losers. That is, any Kaldor-Hicks efficiency gain can be made into a Pareto improvement, if the right transfers are made in the background. A regressive tax could be combined with tax reform so as to preserve the desired income distribution, or any firms facing lost profits can be made whole.

The task of designing and implementing the right background transfers or reforms, however, may often be impossible when the planner lacks requisite information about the distribution of policy burdens. This paper asks whether or not it is possible to compensate the losers from Pigouvian taxes on externality-causing goods among US households, with a focus on motor fuels. I conclude that Pigouvian taxes cannot create Pareto improvements, and instead that a substantial fraction of households will be made net losers from externality-correcting policies. In brief, Pigouvian taxes create losers.

My focus is on using targeted lump-sum transfers to undo the burden of a corrective tax. In practice, the initial incidence of such a tax will be widely dispersed because consumption and production of goods that create externalities is diffuse. A Pareto improvement requires that some transfer be made to those affected individuals. Given the wide diffusion in externality creation, there are no exogenous characteristics that are sufficiently strongly correlated with externality creation to allow for transfers that will keep all agents whole. That is, the failure to create a Pareto improvement is due to a *prediction* problem; lump-sum transfers can only undo the distribution of burdens if they can be targeted precisely. Barring near perfect predictability, the only way to achieve a true Pareto-improving transfer scheme is to base transfers on the externality-generating activity itself. But, making transfers contingent upon the targeted activity will inevitably create incentive problems that erode the efficiency of the corrective tax.

This paper proceeds by laying out a theoretical framework that derives a necessary condition for a Pareto-improvement to be possible. I show that, for a Pareto improvement to be feasible, the variables that are used to determine the transfer program must precisely predict baseline consumption of the externality-causing good, with the degree of precision related to the size of the surplus gain created from externality reduction. This in turn depends on the marginal social damages and the own-price demand derivative for the good. To check whether this necessary condition holds for an empirical application, one therefore needs (1) an estimate of the distribution of baseline consumption of an externality-creating good, (2) knowledge of the correlation between baseline consumption and covariates that can be used in a transfer scheme, (3) an estimate of the own-price derivative, and (4) an estimate of the size of the externality.

To take the theory to data, I use the Consumer Expenditure Survey (CEX) to estimate the distribution of consumption of externality-creating goods and the correlation between consumption and covariates that could be used in transfer schemes. I combine this with estimates from the literature of the size of externalities and price derivatives. I initially focus on a gasoline tax used to correct carbon-related externalities. There is wide dispersion in consumption of gasoline across households, and only a modest fraction of this variation is correlated with variables that are likely to influence a transfer scheme, namely household structure, geographic location and income. Only about one-third of intrahousehold variation in annual gasoline expenditures is predictable by those variables, based on OLS and Lasso models. Using conventional estimates of the externality gain achieved by a carbon tax, I conclude that the transfer scheme is nowhere close to precise enough to create a Pareto improvement (i.e., the necessary condition does not hold). Instead, in the most saturated model, I find that more than one-third of households are net losers.

Additional variation can be explained with correlated endogenous variables. Specifically, vehicle ownership variables predict some of the remaining variation in gasoline expenditures, as one would expect. Conditioning transfers to recycle the gasoline tax on vehicle ownership is clearly problematic in terms of incentives, but even using these variables only pushes the explanatory power up by a modest amount and leaves a large number of losers. (Even the preferred schemes involving demographics and income create incentive effects, as those characteristics will, to varying degrees, respond to the transfer scheme. In abstracting from these distortions, I am painting an optimistic picture for targeting, which still falls far short of creating a Pareto improvement.)

I then show that the degree of predictability is no better for other externality-causing goods measured in the CEX, namely natural gas, electricity, alcohol and tobacco. I interpret this as evidence that it will be infeasible to create a Pareto improvement from corrective taxes on these goods, even when a planner uses an implausible amount of information to create an unrealistically flexible lump-sum transfer scheme.

The theory and prediction exercise in this paper are focused on the narrow question of whether it is possible to compensate all losers from a corrective tax. But I also aim to make a broader point about how an empirical prediction problem lies at the heart of traditions in public finance that suggest efficiency and distributional concerns can be separated in policy analysis. A tradition in economics going back at least to Musgrave (1959) suggests that efficiency and equity concerns can often be conceptually divided. Given tools that can tilt the balance between rich and poor, like a progressive income tax, a policymaker should ensure market efficiency, and then simply dial up (or down) the levers that determine the income distribution to achieve the desired resource allocation in society. This is an extremely useful modeling device, and it is favored by many who study second-best tax design (e.g., Kaplow 2004). A literature in public finance explores the separability of efficiency-enhancing policies, including Pigouvian taxes, in second-best constrained environments (e.g., Gauthier and Laroque 2009; Kaplow 2012). This theoretical literature has noted that preference heterogeneity is a critical assumption in their models, but little empirical work follows up by asking how these ideas can be implemented when there is some heterogeneity. Similarly, a seminal result of optimal tax theory is that the distributional implications of a commodity tax are irrelevant in the presence of a nonlinear income tax (Atkinson and Stiglitz 1976), but this likewise requires preference homogeneity (Saez 2002). The present work comments on these theoretical traditions by (1) highlighting the role of empirical prediction of heterogeneity in this separation, (2) theoretically demonstrating how Pareto improvements can accommodate mild preference heterogeneity, and (3) empirically testing the degree to which transfers can be adequately targeted so as to undo the initial distributional burdens of a class of policies.

Should we be concerned about creating a Pareto improvement, or is it a red herring? Pareto efficiency vis-à-vis the status quo is quite distinct from social welfare maximization.[1] If one begins with the objective of maximizing social welfare, there is no reason to prioritize the status quo resource allocation in society, so fussing over Pareto improvements is largely a distraction. The motivation for seeking Pareto improvements in this paper is instead a practical one. The political process tends to favor the status quo over changes, and as such, affecting change requires satisfying a great many people. That is, a utilitarian planner would gladly accept a policy that benefits most people, but causes modest harm to the remainder. But, in practical terms, even small numbers of losers can create substantial political obstacles, consistent with the logic of collective action (Olson 1965, 1982). Empirically, this paper suggests that even implausibly well-designed schemes will leave large fractions of households

[1] See Kaplow and Shavell (2006) for a view that favors de-emphasizing fairness and focusing solely on welfare maximization. My difference in perspective is based on a concern for practical implementation of policy, not a difference in normative theory.

as net losers. With this in mind, the final section of this paper suggests several ways that an empirical prediction problem can be adapted so as to inform the design of a "politically optimized" transfer scheme that accompanies a Pigouvian tax.

The paper contributes most directly to an existing literature on the distributional impacts of gasoline taxes (e.g., Poterba 1991; West 2004) and carbon taxes (e.g., Hassett, Mathur, and Metcalf 2009; Grainger and Kolstad 2010; Dinan 2012; Mathur and Morris 2014; Metcalf 2009; Burtraw, Sweeney, and Walls 2008; Williams, Gordon, Burtraw, Carbone, and Morgenstern 2015). That work has been overwhelmingly focused on measuring *average progressivity/regressivity* of taxes, whereas this paper is sharply focused on heterogeneity in policy burdens conditional on income and the degree to which that heterogeneity can be controlled via a transfer scheme.

A smaller recent literature does quantify heterogeneity in policy burdens conditional on income. Rausch, Metcalf, and Reilly (2011) use the Consumer Expenditure Survey (CEX) to characterize the overall progressivity of carbon pricing, accounting for both consumption and income channels. Pizer and Sexton (2019) analyze the CEX and similar data from the United Kingdom and Mexico to show box plots that depict the range of energy consumption within income deciles. Fischer and Pizer (2019) explore how attention to horizontal equity influences a comparison between energy-pricing schemes and a performance standard. Cronin, Fullerton, and Sexton (2019) link the CEX to income tax data to explore a variety of revenue recycling mechanisms and quantify the variation in burdens that remains, taking into account fine-grained differences in income sources. Davis and Knittel (2019) show the heterogeneity in policy impacts of fuel-economy standards across different households in the same income decile in what is otherwise a study of average progressivity.

These papers provide several initial results that are important for the development of a full analysis of heterogeneity in the incidence of energy policies. All demonstrate that there is significant heterogeneity in baseline energy consumption within households that have similar income, which are consistent with the descriptive facts I document here. Only Cronin, Fullerton, and Sexton (2019) link their study of heterogeneity to revenue redistribution schemes. They model several realistic schemes for revenue redistribution using detailed administrative tax records to show how the distribution of burdens depends on the use of revenue. I complement their approach first by modeling alternative transfer schemes that are explicitly designed to reduce heterogeneity in burdens, and second by providing a theoretical framework that demonstrates under what conditions revenue redistribution could plausibly achieve a Pareto improvement.

Many prior studies have discussed compensation schemes from externality-correcting taxes, and careful writers do sometimes note that schemes that achieve average redistributional goals will nevertheless create some losers (e.g., Metcalf 2018). Cronin, Fullerton, and Sexton (2019) and Fischer and Pizer (2019) both mention that, when there is a great deal of heterogeneity in baseline energy usage, it will be impossible to design transfer schemes to make everyone better off. They assert this, but they do not in fact test it. I develop a model that demonstrates under what conditions this claim will hold, and I then test this claim empirically.

Another related strand of literature focuses on compensating producers who are harmed by environmental regulation (Bovenberg and Goulder 2001; Bovenberg, Goulder, and Gurney 2005; Goulder, Hafstead, and Dworsky 2010). Most of that literature focuses on average impacts by industry or consumer group and does not delve into the heterogeneity that is the core of this study, though Burtraw and Palmer (2008) do consider individual power plants in an examination of the impacts on the electricity sector.

2 A model of Pareto transfers

A deliberately simple model is developed here to fix ideas and illuminate core insights. The goal is to derive a necessary condition for creating a Pareto improvement from a Pigouvian tax that can be taken directly to data.

The economy: Consider an economy with a good q that causes a negative externality and a quasi-linear numeraire. Heterogeneous agents, indexed $i = 1, ..., N$, have exogenous and potentially heterogeneous incomes and heterogeneous utilities over q. Consumers are "small"—they assume their actions have no impact on aggregate outcomes. Preferences and income result in demand curves written $q_i(p+t)$, where p is the market price and t is any tax levied on the consumption of the good. The supply of q is assumed to come from a perfectly competitive market with constant returns to scale. The full burden of any tax is thus born by buyers. Demand for q_i is assumed to be nonnegative. Denote the baseline consumption of the good (demand when taxes are zero) as $\tilde{q}_i \equiv q(p)$.

The externality: The externality is global, homogenous and linear, so that the total social damages depend on only the aggregate consumption of q, which is written as $Q \equiv \sum_i q_i$. Marginal damages per unit of Q are the sum of marginal damages to each individual, denoted ϕ_i. The aggregate marginal harm of the externality is $\Phi \equiv \sum_i \phi_i$. The total externality in the economy is thus ΦQ.

The tax: In this setting, the first-best outcome can be achieved through a standard Pigouvian tax on consumption equal to $t = \Phi$. Rather than that tax, I model here the introduction of an infinitesimal positive tax, starting from zero. This marginal analysis simplifies exposition and is conservative against the main point of the paper—it will be easier to create a Pareto improvement from this marginal tax than from the full Pigouvian tax because the marginal tax maximizes the ratio of welfare gains to tax burdens. The same steps can be followed for a "small" tax using standard triangle approximations.

The effects of the tax: The higher price of q causes each consumer to lose private surplus. This loss is denoted c_i. For an infinitesimal tax, this loss is equal to baseline consumption, $c_i = \tilde{q}_i$, by Roy's identity. Consumers with higher baseline consumption experience a greater welfare loss. The total surplus loss is $C = \sum_i c_i$.

The tax also raises revenue from each consumer, denoted r_i. For an infinitesimal tax, the revenue raised is equal to the burden, so that total revenue $R = C$.

Finally, the tax creates a welfare gain equal to $\Phi \sum_i q_i' \equiv \Phi Q'$, where q_i' is the derivative of demand with respect to price for each consumer and Q' is the aggregate demand derivative. Each consumer experiences gains from the externality reduction, denoted $g_i = -\phi_i Q'$.

The transfer function: Revenue is recycled in a transfer scheme T that is assumed to be lump-sum and based on a vector of covariates $\mathbf{X}_i$. The idea is that a transfer function will depend on some characteristics (age, income, etc.). The transfer function cannot be tailored to each individual, but instead can only be targeted based on those variables. I focus on the case where all revenue is recycled, so that $\sum_i T(\mathbf{X}_i) = R$. Alternatives are discussed below. In order to match the empirical application, I assume that $T(\mathbf{X}_i)$ is linear in parameters.

A Pareto improvement: A Pareto improvement occurs when the transfer to each person exceeds their net burden and the budget constraint holds; that is:

$$T(\mathbf{X}_i) + g_i > c_i \ \forall i \quad \text{and} \ \sum_i T(\mathbf{X}_i) = R.$$

The main result: Condition 1 is a necessary condition for a Pareto improvement to be possible. It directly motivates empirical analysis. Intuitively, the condition shows that Pareto improvements are more difficult as transfer schemes are less able to precisely target tax burdens and less difficult as efficiency gains from the tax are larger.

Condition 1. *Let c_i be the private surplus losses from a marginal tax, N be the number of agents, $T(\mathbf{X}_i)$ be a transfer scheme that recycles all of the revenue from the tax, and g_i be the externality gains, where $g_i \geq 0 \ \forall i$. A Pareto improvement is not possible if the average absolute errors exceed twice the average surplus gain; i.e., a Pareto improvement is not possible if*

$$\frac{1}{N} \sum_i |c_i - T(\mathbf{X}_i)| \geq \frac{2}{N} \sum_i g_i.$$

Condition 1 illustrates the relationship between the size of the surplus gain and the ability of a policy to precisely target transfers based on initial burdens. The precision of targeting is summarized by the size of the absolute difference between the initial burden c_i and the transfer $T(\mathbf{X}_i)$, which I refer to as the error.

To build intuition, consider first outcomes that ignore the gains g_i. Whatever allocation scheme is used will produce some differences between initial burdens c_i and transfers $T(\mathbf{X}_i)$. For a marginal tax, the burdens c_i total to available revenue R. Thus, before considering gains, a weak Pareto improvement is possible only if all revenue is dispersed and all transfers are exactly equal to initial burdens for each individual; i.e., if $c_i - T(\mathbf{X}_i) = 0 \ \forall i$.

The welfare gains create room for error in the transfer scheme while preserving a Pareto improvement. Specifically, suppose that the welfare gains g_i are distributed perfectly to offset the losses to any losers. Then, the total surplus available G acts as an "error budget". Condition 1 characterizes the maximum losses among losers that could be overcome by surplus gains, *assuming the surplus gains are allocated perfectly so as to offset losses*. Because there is no reason to believe that surplus gains will be distributed in this perfectly convenient way, the condition is a necessary condition, not a sufficient one, and a generous one at that.

Alternative conditions could be derived, but this formulation is appealing both because it is a particularly simple way of highlighting the relationship between heterogeneity, predictability and the size of welfare gains, and because it requires a minimum of information to be tested empirically. It requires only information about baseline consumption of the good and the total surplus gain, which depends on only the aggregate demand elasticity and marginal damages. In particular, condition 1 makes no assumption about the distribution of gains g_i, except that all are positive. (The positive gain assumption is not economically substantive, but it is required for the particular algebraic proof used.) It may often be the case that externality gains are known on average, but the distribution of them is difficult to estimate. The necessary condition here does not require information about how the gains are distributed.

To create a Pareto improvement, one is concerned only about the size of errors among losers, yet the condition is formulated based on the absolute error, which attends to both winners and losers. Against a budget constraint, there is a symmetry to errors for winners and losers—overcompensating a winner uses up surplus that cannot be transferred to a loser. In addition, the average absolute error formulation relates more clearly to empirical regression analysis than a formulation based only on errors to losers.

The condition is relevant for any arbitrary transfer scheme $T(\mathbf{X}_i)$. The empirical portion of this paper will try to predict initial burdens c_i with a set of covariates $\mathbf{X}_i$. Such a prediction exercise can then be mapped into a targeted transfer scheme. For any proposed transfer scheme, one can calculate the average absolute errors and check if the necessary condition is met. If a regression approach that minimizes the size of absolute errors (median regression) fails to generate an average absolute error small enough to satisfy the condition, then it is concluded that no feasible (i.e., based on the available covariates) transfer scheme can achieve a Pareto improvement.

In sum, condition 1 illuminates how the design of a Pareto improving transfer scheme is inherently a prediction problem. If the variation in tax burdens can be predicted accurately enough, then a Pareto improvement might be possible. What is "accurate enough" depends on the size of surplus gains—where surplus gains from a policy intervention are small, either because the externality is small or because quantities are not very sensitive to price, the accuracy window will be tight.

2.1 The models assumptions are biased towards enabling a Pareto improvement

The model makes a number of assumptions to deliver a tidy result. Most are easy to relax and are biased against the paper's main findings. I discuss them here before proceeding to the empirical analysis. Some cases where a Pareto improvement might be more feasible are discussed in section 5.

Starting from a pre-existing tax: The derivation assumes a zero marginal tax. This ensures that the initial consumer burdens are exactly offset (on average) by the revenue raised ($C = R$). Suppose instead that a tax exists, but that the tax is below marginal damages so that an increase is efficiency enhancing. The analysis can proceed by simply reinterpreting the externality gain as the difference between marginal damages and the existing tax rate (i.e., the uncorrected portion of the externality). The only difference is that, in this case, a marginal increase in the tax will create initial consumer burdens that are in excess of revenue raised ($C > R$). In terms of the model, this shrinks the net efficiency gains available, thereby shrinking the margin for error in targeting. This makes achieving a Pareto improvement even more difficult.

A non-marginal tax: The derivation assumes a marginal tax. For a non-marginal tax increase, burdens will again exceed cost. Just as in the case above, this effectively shrinks the net surplus, thereby shrinking the margin for error in targeting. This makes achieving a Pareto improvement even more difficult.

Heterogeneity in behavioral response: For a non-marginal tax or when the initial tax is above zero, the behavioral response (the own price demand elasticity for the good) will figure into the burden calculation (i.e., the envelope condition does not apply). Where demand derivatives are homogenous, no new information is required to conduct an empirical test in these cases. But, if demand derivatives are heterogeneous, then in principle information about the joint distribution of baseline consumption and demand derivatives is needed to calculate the distribution of burdens. This complicates empirical tests of the condition, but just as significantly, it greatly magnifies the real world task of compensating losers. It will frequently be easier to measure baseline consumption than to also estimate behavioral responses. Where the initial burden of a policy is harder to measure, the task of identifying and compensating losers will be even more difficult.

Gains outside of market: The model assumes that the efficiency gains accrue to the consumers of the good. If the gains accrue somewhere else (i.e., among future generations for a carbon tax), then the challenge is even greater because those gains must be taxed back in order to sustain transfers to the losers. If some fraction of the gains accrue to the consumers of the good and one wishes to ignore gains accruing to others, the existing analysis can be used as is with the gains g_i interpreted as the portion of efficiency gains enjoyed by consumers of the good.

Incidence (partial equilibrium): The model assumes complete pass through of prices to consumers and assumes that welfare can focus on only consumers. Where producers of the good also bear the burden, pass-through estimates are needed to divide up gains and the planner must consider targeted allocations on both sides of the market. The problem is otherwise the same. (Note that heterogeneity in pass through (for an example of which, see Stolper (2018)) would further raise information requirements.)

Incidence (general equilibrium): Corrective taxes can create burdens through a variety of general equilibrium effects and other channels (Fullerton 2011). For example, a carbon tax will affect factor prices. These general equilibrium effects may be substantial and heterogenous across groups (see e.g., Goulder, Hafstead, Kim, and Long 2018). The partial equilibrium focus in this paper is motivated in part by practicality, but to the extent that the exercise is motivated by political economy concerns, this limited partial equilibrium view is likely the important one. If voters are unable to anticipate general equilibrium incidence effects, it is likely that they heavily discount them in forming their judgments about how a policy will affect them. The immediate impact on prices and any promised transfer scheme are likely the dominate consideration.

Measuring burdens and gains: This last point segues to a broader point that the full benefits (as well as the costs) of any externality correcting tax are difficult to measure. This is a challenge for the econometrician, but the challenge is just as great for the planner and the voter, which reinforces the core point of this paper. When the planner cannot measure the benefits or costs, it is no more possible to control the final distributional effects. And, when benefits and costs are difficult for the voter to perceive, it will be difficult to convince everyone that they are in fact benefitting. (Of course, if they can be fooled, then perhaps the political problem can be solved through deception rather than targeted transfers.)

3 Consumption data on externality-generating goods

This paper uses data from the interview portion of the Consumer Expenditure Survey (CEX), which is a nationally representative sample of U.S. households, from 1996 to 2016.[2] The CEX defines a unit of observation as a consumer unit, which is a set of individuals who reside together and are either related by blood or marriage, or who make financial decisions together.

Interviews consist of retrospective questions that ask about the consumer unit's total expenditures on various items over the prior three months. Units are interviewed four times, once each quarter, but not all units complete all four rounds of interviews. For the analysis below, expenditure categories are averaged over however many interviews are completed by a consumer unit, and then scaled to represent annual consumption amounts.

Table 1 shows summary statistics on expenditures. Key for this paper is that there is wide variability in the consumption of all variables. For example, average consumer unit expenditures on motor fuels is $1,746, but the standard deviation is nearly as large as the mean, at $1,529.

There are two important caveats to be kept in mind regarding the use of the CEX in this study. First, the analysis is concerned with variance and predictability of consumption levels across households. The survey response may mismeasure true consumption either because of sampling variability or because of inaccuracies in self-reported responses. For a discussion of CEX data quality, see Meyer, Mok, and Sullivan (2015). Throughout the paper, I winsorize all expenditure variables at 1% in order to trim the influence of outliers. Data quality remains a concern, but it turns out that the expenditure data reported here implies almost exactly the same mean gallons per year estimates as the 2009 National Household Travel Survey, which provides some reassurance. Further comparisons of the data are included in the appendix B.

Second, the CEX reports expenditures, not quantities. Externality-correcting policies are typically specific taxes (per unit) not ad valorem. To model an ad valorem tax on a product, only the total expenditure is required. Corrective taxes, however, will often take the form of a specific (per unit) tax. For example, a carbon tax will raise the price of gasoline

[2] The CEX is actually two distinct surveys drawn from different samples of households, called the interview and diary surveys. The diary survey is less appropriate for current purposes where the focus is on variation across households because it records expenditures over a single week, so that variation in diary expenditures might simply reflect variation in timing of spending, rather than overall levels.

Table 1: Household expenditure statistics by category

	Mean	Median	St. Dev	CV	Pct 0
Motor fuels	$1,746	$1,353	$1,529	0.9	9%
Electricity	$1,143	$984	$913	0.8	9%
Natural gas	$413	$162	$611	1.5	42%
Alcohol	$219	$15	$401	1.8	47%
Tobacco	$296	$0	$648	2.2	72%
All energy	$3,306	$2,919	$2,226	0.7	3%
All sin goods	$3,821	$3,388	$2,493	0.7	2%

Table shows annualized expenditures by category for all households in sample (N=197,668). Dollar amounts are in $2015. All energy sums motor fuels, electricity and natural gas. All sin goods includes all five individual categories summed.

Table 2: Summary statistics of demographic variables

	Mean	St. Dev.	Min	Max
Before-tax income ($2015)	59,220	61,680	-419,200	971,100
After-tax income ($2015)	55,840	57,430	-421,300	961,700
Consumer unit (CU) size	2.4	1.5	1	29
Persons < 18 in CU	0.62	1.1	0	14
Persons >64 in CU	0.28	0.6	0	8
In MSA indicator	0.83	0.38	0	1
Urban indicator	0.91	0.29	0	1
Reference person married	0.50	0.50	0	1
Year	2006	6.1	1996	2016

by a constant amount per gallon. Thus, to model the impact of a carbon tax on gasoline consumption, we need to estimate the gallons of gasoline consumed by a household, based on their reported expenditure and prices.

For gasoline and diesel fuels, I use data from the Energy Information Administration (EIA) on the sales-weighted, tax-inclusive, retail price of all grades of each fuel type at the closest available geographic match to the consumer unit. That is, where the CEX identifies a consumer unit's metropolitan statistical area and the EIA has city-specific prices, the consumer unit is assigned prices in the past quarter that are the average EIA price for that city. In other cases, matches must be made at the state or PADD level.

For other goods, determining the price paid by consumers is more challenging. Consider alcohol. Prices will vary widely if a consumer unit is purchasing low cost beer or high-end Scotch. As a result, for goods other than motor fuels, I focus on predicting expenditures directly (rather than predicted tax burdens), which translates directly to taxes under an ad valorem tax, recognizing that this is not how a true Pigouvian tax would be designed.

The core empirical task in the paper is to determine the degree to which demographic variables that might plausibly be used in a transfer function are able to predict variation in expenditures across consumer units. Table 2 summarizes the key variables used for this purposes, which are measures of income, household size and location.

4 A gasoline tax creates losers

The primary empirical application of this paper is a gasoline tax, which is modeled here as an efficient carbon-correcting policy. This is an important policy in its own right, and also has advantages in terms of modeling and measurement with the CEX. The conceptual goal of this analysis is to analyze an optimally designed Pigouvian tax. I thus focus on the gasoline tax as a well-targeted policy for correcting carbon externalities, but I discuss the implications of other driving-related externalities in the robustness section below.

In this section, I calculate the relative magnitude of welfare gains as compared to revenue raised from a motor fuel tax, and then demonstrate the degree to which demographic variables can predict motor fuel consumption. Specifically, I model a small tax increase of 10 cents on motor fuels (both gasoline and diesel) under the assumption that the carbon externality from motor fuel consumption is not corrected at all prior to the tax. That is, I am interpreting existing gasoline and diesel taxes as having been motivated by considerations about the optimal way to raise revenue, irrespective of a carbon externality. These assumptions are designed to be conservative against my findings, as they will maximize the implied welfare gains from carbon taxation.

In the analysis, I abstract from concerns about the tax interaction effect, through which a tax on gasoline is expected to create additional distortions by lowering real factor returns (Goulder 1995; Bovenberg 1999). I again interpret this abstraction as conservative against my results, as the tax interaction effect will imply that net welfare gains from correcting the externality are smaller.

4.1 What are the carbon externality gains from motor fuel taxation?

As described in the model, the welfare gain from a small tax on gasoline will be equal to the change in gasoline consumption induced by the tax times the externality per gallon. I assume that in the long run a gasoline tax will be born completely by consumers so that prices will rise by 10 cents per gallon.[3]

The gasoline demand literature typically estimates elasticities, so I translate the 10 cent gasoline hike into a percentage price change using the average retail gasoline price facing the consumer unit at the time of the survey in its geographic location. I then use a gasoline price elasticity of -0.4, which is interpreted as a long-run price elasticity, to translate this price change into a change in gallons of fuel consumed.[4] By its very nature, it is challenging to estimate the long-run price elasticity of gasoline. I experiment with alternative values below.[5]

I use the EPA's conversion factor to determine the tons of carbon emitted per gallon of gasoline consumed (17.6 pounds per gallon / 2205 pounds per metric ton for E10, or 22.5 pounds per gallon / 2205 pounds per metric ton for diesel) and then multiply by $40 for the social cost of carbon.

[3]Existing studies find evidence of high pass through rates for state gasoline taxes, with many studies consistent with full pass through Chouinard and Perloff (2004, 2007); Doyle and Samphantharak (2008); Marion and Muehlegger (2011). Fewer studies consider the federal gas tax, perhaps because it has changed much less often, which impedes econometric investigation. (Chouinard and Perloff 2004) conclude that only half of a federal tax increase is born by consumers. If true, it would be important to consider the incidence on U.S. households through the producer side in interpreting the estimates. I return to this issue when discussing the empirical results.

[4]Small and Van Dender (2007) estimate long-run elasticities closer to half this magnitude. Hughes, Knittel, and Sperling (2008) conclude that the elasticity has been declining over time, finding preferred estimates well below -0.4. Espey (1998) finds a range of estimates that extend well beyond -0.4 in magnitude, but this is based on a variety of studies with varying credibility of empirical strategy. There is some suggestion that demand might respond more to gasoline taxes than price variation (Davis and Kilian 2011; Li, Linn, and Muehlegger 2014), though these estimates, taken from monthly changes in consumption, may be due inflated estimates due to consumers pre-buying in anticipation of price changes (Coglianese, Davis, Kilian, and Stock 2017). This difference seems unlikely to persist in the long run.

[5]I assume a homogeneous elasticity. Simple back of the envelope calculations make clear that allowing for heterogeneity will have little impact on the qualitative results.

All of the assumptions here are designed to be generous in favor of creating larger externality benefits, and using the global social cost of carbon is foremost in that generosity. Climate benefits are largely realized in the future, and the majority of benefits will be realized outside of the U.S. Indeed, the current administration advocates use of a domestic social cost of carbon ranging from $1 to $6 in rule making. Thus, while there is vigorous debate about the right estimate of the social cost of carbon, it is exceedingly likely that $40 per ton exaggerates the benefits that accrue to current U.S. drivers.

4.2 Externality gains are much smaller than the initial burden and revenue raised

Because I am modeling a small gasoline tax, the initial burden (loss of consumer surplus from the higher price) will be approximately equal to the revenue, both of which are simply the price increase times the number of gallons of gasoline consumed by the consumer unit. But, to be more precise, I use the elasticity estimate to calculate the final quantity consumed, and use that to calculate revenue. The welfare loss is calculated using a linear approximation. Specifically, revenue raised from each household is equal to 10 cents times the new consumption level, which is equal to the current observed of consumption (from data) minus the elasticity (-0.4) times the implied change in price (current price plus 10 cents divided by the current price, all minus 1). The initial private welfare loss is calculated as the new consumption level (as described above), plus the triangle, which is the change in consumption (as described above) times 1/2 times the tax (10 cents).

According to these calculations, the externality gains are $8.25 per consumer unit per year on average, while the revenue raised is $90.00 per consumer unit per year. The revenue raised is an order of magnitude larger than the externality gain. This has an important implication for the ability of the planner to create a Pareto improvement because, as shown by the theory, the externality gains represent the "error budget" available. A large amount of revenue needs to be reallocated via a transfer function, and the error budget is small relative to the revenue raised. This implies that the revenue must be allocated very precisely.

4.3 Most variation in burdens is not predictable

The key suggestion of the theoretical model is that the degree to which the initial (pre-transfer) burden of the corrective tax can be predicted by variables that are used in the transfer function will determine whether a Pareto improvement is technologically feasible. Simple regression of the household level burden on variables that constitute the transfer function thus provide the required estimates. Below, I present results where the left-hand side variable is the estimated household level initial burden of a 10 cent gas tax.[6] All values are inflation adjusted to 2015.

The theory involves non-squared errors, so I present least absolute deviation (LAD) regressions that will minimize non-squared errors. But, I also present parallel specifications from OLS because the properties of OLS and the R^2 goodness of fit statistic is most familiar. Note that LAD will, by definition, yield lower absolute errors, but OLS, by definition, will maximize the R^2.

Table 3 presents the primary estimates from this exercise. All regressions include year of sample fixed effects, which account for any time trends, though it turns out that excluding them has almost no impact on the results. Designing a transfer scheme that depends on any variables that are not strictly exogenous will create distortionary incentives. As a result, I focus attention first on the "most exogenous" variables that are likely components of a tax scheme, which are demographic indicators for household structure and geographic indicators for state and urban versus rural. Specifically, regressions include state dummies, dummies for an urban indicator and an MSA indicator, and dummy variables for the number of people in the household, as well as the number of minors, and the number over age 60. These variables predict a just under 30% of the variation in gasoline tax burdens (which is approximately the same as baseline consumption).

Column B adds a linear income control, followed by a non-parametric function of income (dummies in five-year bins) in column C. These provide a modest boost in the explanatory power, with the R^2 bumping up to .331 and .356, respectively. For reference, income by itself, without any demographic or geographic variables, explains only about 15% of variation (results not shown). Column C is my preferred specification. It is based on characteristics that are already part of the tax system, and could plausibly be used to design a tax reform or transfer scheme that accompanies an externality-correcting tax.

The unexplained variation in this specification is far too large to achieve a Pareto improvement. The average absolute error allows for direct comparison with the welfare gains from the externality. The residuals are around \$45 per household. This compares to the \$8.25 welfare gain. This is directly related to Condition 1: as long as the absolute average error exceeds the welfare gain, a Pareto improvement is not possible. Moreover, it is not just a matter of a few people being left as net losers. The best fitted scheme leaves more than one-third of households as net losers, even with the generous assumptions employed throughout.

Column D adds some clearly endogenous variables that would create significant distor-

[6] Because I am assuming a homogenous elasticity across households, this is equivalent to using initial baseline consumption (in gallons) as the left-hand side variable.

Table 3: Predictability of Motor Fuel Tax Burden (OLS)

	A	B	C	D
Avg. Abs. Error	\$46.6	\$45.0	\$44.2	\$39.9
R^2	.292	.331	.356	.456
N	197,668	197,668	197,668	197,668
Year FE	Y	Y	Y	Y
Demo & geo controls	Y	Y	Y	Y
Linear income		Y	Y	Y
Binned income			Y	Y
Vehicles & energy				Y

Table 4: Predictability of Motor Fuel Tax Burden (LAD)

	A	B	C	D
Avg. Abs. Error	\$45.7	\$44.1	\$43.2	\$38.8
N	197,668	197,668	197,668	197,668
Year FE	Y	Y	Y	Y
Demo & geo controls	Y	Y	Y	Y
Linear income		Y	Y	Y
Binned income			Y	Y
Vehicles & energy				Y

tions and are thus likely problematic variables for inclusion in a transfer scheme, including home energy consumption and dummies for the number of vehicles owned by the household, and dummies for the number leased. These variables do provide an additional boost to explanatory power, but even with vehicle ownership variables included, the variables explain less than half of the variation.

Table 4 shows LAD specifications. As expected, these lower the absolute error for identical specifications, but only by a very small amount. Figure 1 shows the distribution of net losses, accounting for both the externality gain and the targeted transfers, based on column C in Table 3. A full 37% of households remain as net losers under this scheme.

The variables chosen here are the ones that are most likely to be used for a transfer scheme that operates through the tax code. The tax code is essentially a function of income and demographic structure of the household. As such, I interpret the results of Tables 3 and 4 as demonstrating that gasoline expenditures are not predicted well enough to come re-

Figure 1: Net Loss from 10-cent Gasoline Tax with Targeted Transfer

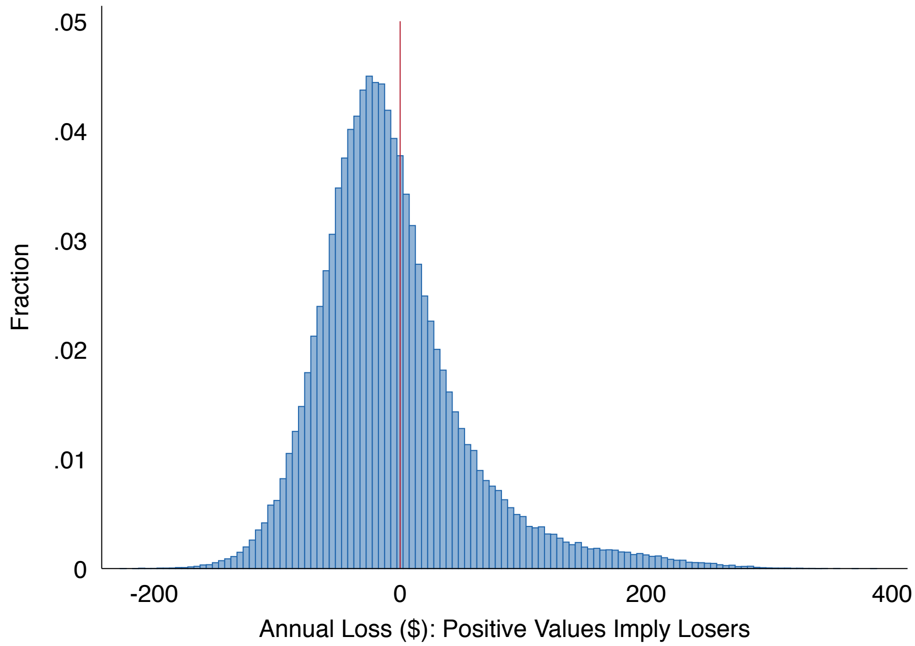

Figure shows the distribution of net impacts of a 10-cent gasoline tax, in dollars per year. A positive value implies a welfare loss. The transfer scheme used is based on the last column of Table 3, using specification C. The net impact is the private welfare loss, net of the targeted transfer scheme, net of the externality gain.

motely close to enabling a Pareto improvement. A Pareto improvement is not technologically feasible.

4.4 Machine learning marginally improves prediction

The problem posited here is fundamentally a prediction problem. This is therefore a natural application for machine learning. Table 5 reports results from an exploration of problem of predicting gasoline tax burdens using Lasso. These results are based on a 20% sample of the data.[7] The first column repeats column C from Table 3 on the 20% sample, which delivers nearly the same average absolute error and R^2.

The second column is a Lasso analysis that uses cross validation to eliminate overfitting, run on the same set of possible covariates that are included in the first column. Lasso drops a number of explanatory variables, but in doing so barely changes the R^2 and average absolute error. This suggests that overfitting is not causing a significant bias in the main results.

The third column then allows for a large number of interactions, including year dummies

[7]Additional exploration, including random forest analysis, is in progress.

Table 5: Lasso regressions on gas tax burden

	OLS (C)	Lasso	Lasso
Avg. Abs. Error	\$43.5	\$43.6	\$43.2
R^2	.359	.354	.365
Vars. Supplied		178	7,844
Vars. Selected		129	433
N	39,534	39,534	39,534
Year FE	Y	Y	Y
Demog. & geog. controls	Y	Y	Y
Linear income	Y	Y	Y
Binned income	Y	Y	Y
Exogenous interactions			Y

interacted with the \$5k bin income dummies, and geography and demographic dummies interacted with the income dummies. These additional variables provide only a modest boost to explanatory power. Other initial explorations have similarly found that significantly expanding the set of explanatory variables, based on what is available in the CEX, has limited ability to explain the remaining cross-household heterogeneity in motor fuel consumption. In other words, the main results are robust to (preliminary) machine-learning analysis.

4.5 Robustness to parameter choices

In this section, I present results that alter three assumptions about the data. First and most simply, I increase the number of data points that are winsorized. Second, I modify the elasticity of gasoline consumption from -0.4 to -0.6 and then -0.8, to reflect higher estimates from the literature. Greater elasticities are important because they will lead to greater welfare gains, which aids the elimination of losers. Third, I greatly increase the externality per gallon of gasoline consumed, from around \$0.31 to \$2.

The higher latter number is based on accounting for non-greenhouse gas emissions from motor fuel consumption. Harrington, Parry, and Walls (2007) survey the literature and conclude that greenhouse gas emissions externalities are quite modest compared to accident and congestion externalities. A gas tax is a very poor instrument for targeting congestion, and a mediocre at best instrument for targeting accidents or local air pollution. Nevertheless, I now show cases where the gas tax could have much larger benefits in order to compare results.

In arriving at a \$2 per gallon externality, I modify the values from Harrington, Parry, and Walls (2007) to account for a higher accident externality, at \$0.91 per gallon based on

Table 6: Fraction of losers under alternative assumptions

Elasticity	Externality per gallon	Percent Windsorized	Percent Losers
-0.4	$0.31	1%	37.0%
-0.4	$2	1%	15.5%
-0.6	$2	1%	9.7%
-0.8	$2	1%	6.2%
-0.8	$2	10%	3.0%

Anderson and Auffhammer (2014), but interpret the carbon benefits as negligible. I then subtract off the sales-weighted average gas tax in the US of $0.48. In terms of the literature on second-best gasoline taxes, however, note that this is still a generous interpretation in that it ignores fiscal interactions that exacerbate labor market distortions. Parry and Small (2005), for instance, argue that the second-best tax is only around 60% of marginal damages due to fiscal interactions.

Table 6 uses targeted transfers from specification C from Table 3, under alternative assumptions, to calculate the number of households that are net losers. Dramatically increasing the interpreted externality gain per mile roughly halves the number of households who are net losers from a gasoline tax. Increase the elasticity of gasoline consumption to much higher rates further drives down the fraction of losers. In this scenario, the number of net losers is driven down to 6%. This is a modest number, but it should be kept in mind that there are many generous assumptions deployed in this case, so it should be interpreted as a frontier possibility rather than a realistic point estimate. Even in this case, some households are net losers. Finally, taking all of the prior assumptions and also winsorizing a full 10% of the data drives down the number of losers to 3%.

4.6 Other externality-correcting taxes are similar

The focus of this paper empirically is on a gasoline tax, but the CEX enables me to make quick assessment of the degree of predictability of other consumption categories that might be the focus of sin taxes. A gas tax has the advantage that it is relatively easy to translate expenditure data into quantities using gasoline price information, and hence to estimate the impact of a specific (per gallon) gasoline tax. The impact of other sin taxes is more difficult to determine because the goods are more heterogenous (e.g., there are many types of alcohol) and are subject to non-linear prices (e.g., two-part tariffs for electricity and natural gas).

Nevertheless, a broad picture of heterogeneity and predictability can be gained by simply regressing total expenditures in these categories on the demographic variables to see how

Table 7: Predictability of Other Sin Expenditures (OLS)

All statistics are R^2	A	B	C
Motor Fuels	.336	.381	.403
Electricity	.281	.324	.327
Natural gas	.179	.211	.214
Alcohol	.051	.126	.129
Tobacco	.043	.046	.05
All energy	.393	.469	.486
All sin goods	.362	.438	.455
N	197,668	197,668	197,668
Year FE	Y	Y	Y
Demog. & geog. controls	Y	Y	Y
Linear income		Y	Y
Binned income			Y

much of the baseline expenditure variation is predictable. This exercise would exactly mimic the burden of an ad valorem sin tax, and they likely come close to mimicking the scale effect of sin tax levied per unit of the sin good in question.

Note that Table 1 shows that electricity has a similar coefficient of variation with motor fuels, but that other categories have even larger variability. OLS regressions in Table 7 shows the same pattern in terms of predictability. Electricity consumption is very similar in its predictability to motor fuels, but other sin goods are substantially harder to predict.

This analysis is incomplete, as it does not account for the welfare gains and is based on an ad hoc assumption about how a corrective tax would impact prices. But, the results suggest that a gasoline tax is likely the easiest place to achieve broad gains, and that the other externality-creating goods are likely to create even larger numbers of losers because of the greater inability to predict variation in baseline expenditures.

5 Constructive next steps

The thesis of this paper is fundamentally negative. Not all losers can be compensated. This is an important observation, but it is also an unsatisfying place to stop. Several questions suggest themselves as next steps. I explore a few in this section, beginning with a discussion of several situations in which a Pareto improvement might be possible.

But, it is dissatisfying to stop there. Instead, one may wish to identify settings where Pareto improvements are more likely, to formulate second-best allocation schemes that attend more to losers, to develop metrics relative to losers that would guide policy decision making, or to connect targeting schemes back to the original political economy motivation. This section offers observations and first steps in each of these directions.

5.1 When might a Pareto improvement be achievable?

Benefits taxes: If benefits from externality reduction are tightly correlated with the initial burdens of a tax, then there will less variance in the initial burden distribution, making it easier to sustain a Pareto improvement from a tax. As a result, a planner may be much better able to create a Pareto improvement from a benefits tax (i.e., a toll that funds an improvement in a highway) than from the classic externality-correcting taxes emphasized in the empirical analysis. Benefits taxes are often perceived as more fair by voters, which may be related to the issues of compensation described in this paper.

In a related example, Hall (2018) argues that congestion pricing can create a Pareto improvement. This possibility is due in part to the fact that the efficiency gains are closely tied to burdens; those paying a toll are paying directly for the benefit of reduced congestion. (The result is also because the design of the policy sacrifices some efficiency gain in order to achieve the gain. It leaves some lanes unpriced, which preserves a choice to avoid the tax.)

Alcohol, cigarettes and sugary beverages are goods that may lead to externalities, but are often assumed to also be the source of internalities, such that the welfare improvements are concentrated among the heaviest users of the products.[8] (The same is sometimes said of energy-consuming goods, though the evidence of significant behavioral biases is not clear (Allcott and Greenstone 2012).) In this case, the scope for Pareto improvements may be improved.

Distortionary instruments: It is possible to compensate losers in my framework by simply rebating tax revenue according to the initial expenditure levels. But, this will blunt (or completely eliminate) the incentive to correct the externality. Where only a fraction of the revenue need be rebated in this way, it may be possible to create a Pareto improvement that trades off some of the efficiency gain in order to create the Pareto improvement.

More generally, one could perhaps use other variables that are closely correlated with externality-consuming goods in ways that limited choice distortions but favor targeting. For example, vehicle ownership could be included in the transfer scheme, even if gasoline consumption is not. Preliminary results from the CEX suggest that just adding counts of vehicles does little, but one could imagine adding vehicle characteristics, even fuel economy. These variables elevate concerns about "first order" distortions to choice that could greatly

[8] Allcott, Lockwood, and Taubinsky (2018) analyze optimal corrective tax policy in the presence of heterogeneous internalities.

erode efficiency gains. A valuable next research step would be to characterize second-best transfer schemes that are explicit about these distortions. Note that this task requires establishing a social welfare function that puts an explicit value on compensating losers. In practice, this is likely to look like public finance models that include horizontal equity (e.g., Auerbach and Hassett 2002), or that account for status quo allocations (Saez and Stantcheva 2016). The concept of horizontal equity has come under criticism as a normative criterion (Kaplow 1989), but the application here would be based on political constraints, rather than the traditional normative notion to "treat equals equally."

Historical baselines: Another approach is to try to use historical baseline consumption to form the transfer scheme. This is what is often done on the firm side in carbon policies, through free permit allocation schemes. This is harder to envision for households, though not impossible, as it must accommodate entry and exit of households into the economy.

Broader policy packages: The focus of this paper is on considering a single corrective tax and the transfers that can be created with the revenue raised. If such a policy struggles to create a Pareto improvement, it begs the question of whether a broader set of policies considered together can yield a different result (i.e., fewer losers). Multiple taxes taken together may create a less diffuse (or more predictable) distribution of burdens if the consumption of various goods are negatively correlated across agents. The fact that the combined raw energy expenditures are more predictable than each of the categories taken separately hints that this possibility may have empirical relevance.

In the extreme, we could ask if all policy taken together is a Pareto improvement, as compared to a Hobbesian state of nature. This may very well be the case, but the goal here is to focus more practically on a set of real economic policy challenges that are taken up as piecewise legislation.

Another issue is that the revenue could be spent on public goods and services, rather than returned lump sum. Or, it could be used to lower particular taxes. These alternatives would further alter the distribution of burdens. It could be that this creates greater concentration of burdens, but it seems more likely that it creates further dispersion, only making the problem harder.

5.2 Characterizing the trade-off between losses and revenue

This paper focuses on schemes where the budget available for transfers to compensate losers is equal to the revenue raised from the tax. The motivation is that this clearly isolates the possibility of a Pareto improvement, as compared to an identical economy with no corrective tax. In reality, there is no requirement that transfers use all of the revenue, nor is there a prohibition against using extra revenue taken from general funds.

In terms of efficiency, it is well established that all revenue from a corrective tax should be used to lower preexisting distortionary taxes (e.g., see Goulder 1995). As such, using revenue to compensate losers comes at a cost. The presumed benefit is that the policy maker cares about compensating losers, either because of some sense of fairness or simple political expediency.

In this view, a policy maker would want to know how many losers are made into winners, or how much typical losses are reduced, when additional revenue is allocated for transfers. I describe here one way of characterizing these trade-offs that could provide useful information to a policy maker concerned with compensating losers, and illustrate with the data on the gas tax.

I assume that the transfer function would be targeted so as to minimize typical losses for the case where outlays equal tax revenue, and that to scale outlays up or down, the transfer function for all households is scaled proportionally. That is, consider an estimate of the targeting function, $T(\mathbf{X}_i)$ that would be used if all revenue were reallocated to consumers. Then write the total outlays as a fraction of revenue as $\theta = \sum_i T(\mathbf{X}_i)/R$. When $\theta = 1$, all revenue is spent on transfers. When $\theta = 2$, the outlay is double the revenue brought in by the tax.

I assume that individual transfers are all scaled proportionately, so that the transfer to consumer i is $\theta T(\mathbf{X}_i)$. Under this assumption, it is straightforward to characterize the number of losers, the average loss among losers, the variance in loss among losers, or other statistical moments that a decision maker might find useful in deciding how much revenue should be spent on compensation.[9]

To illustrate, I plot the fraction of households who are net losers from the ten-cent gas tax modeled above as a function of the targeted transfer scheme and the outlay ratio θ in figure 2. The solid line shows results assuming that the targeting function is based on the predicted values from the specification in column C of table 3. For comparison, the dashed line shows the same fraction of losers under the assumption that all revenue is returned equally to each household. For either scheme, as expected, the fraction of losers sharply declines as outlays increase. Interestingly, there is little difference between the fraction who are losers between the targeted and untargeted schemes.

The value of targeting is more readily apparent when looking at the distribution of losses among losers as a function of revenue, which is plotted in figure 3. The left panel shows

[9] Proportional scaling may not be the optimal scheme, depending on the rationale for being concerned with losers. It is, however, an intuitive assumption and it is employed here to provide a tractable summary of information that a policymaker might use to make decisions. I discuss optimal transfers further below.

Figure 2: Fraction of Households Who are Net Losers As a Function of Outlay Ratio (θ)

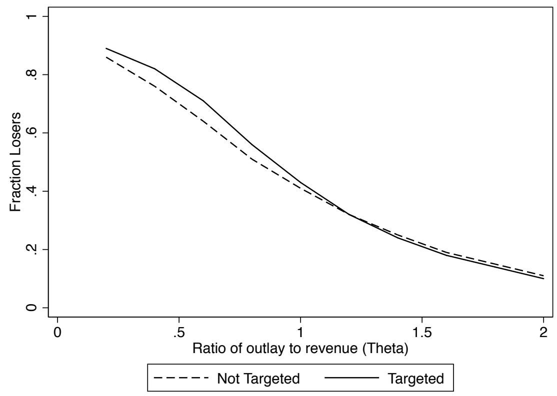

Figure shows fraction of households who are net losers as a function of the ratio of total transfers to revenue. Targeting is based on regression from column C, table 3.

Figure 3: Mean and Standard Deviation of Loss (Conditional on Losing) As a Function of Outlay Ratio (θ)

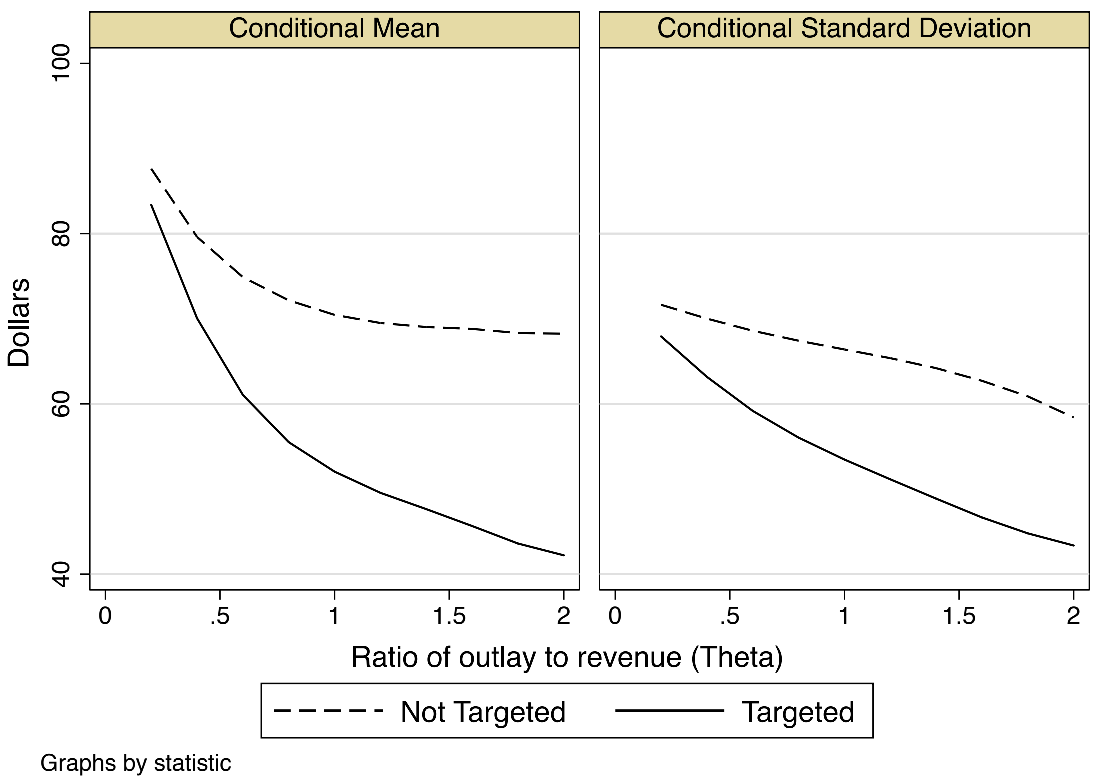

Figure shows mean and standard deviation of household losses as a function of the ratio of total transfers to revenue. Statistics are conditional on a household being a net loser. Targeting is based on regression from column C, table 3.

the average loss (conditional on a household being a net loser). Average losses among losers decline significantly as outlays increase, and they are much lower under targeting. The same is true for the standard deviation in losses (conditional on a household being a net loser), which is shown in the right panel.

As such, comparing the dashed and solid lines illustrates to the planner the value of targeting, and the slopes of the lines capture the trade-off between valuable revenue and compensating losers. For a decision maker concerned with achieving some degree of compensation, these types of statistics can convey valuable information. To fully evaluate alternative transfer schemes and decide how much revenue is worth dedicating to compensation, one requires a model of optimal loser compensation, which I turn to next.

5.3 Towards a politically optimized transfer scheme

This paper is fundamentally an exploration of how targeted transfers can alter the political prospects of efficiency-enhancing policies. The point of this paper is that one easy and appealing political solution—to say that everyone gains—will often be infeasible. Instead, transfer schemes will create winners and losers.

A next step would be to describe the "politically optimal" transfer allocation to accompany a Pigouvian tax (i.e., what is the transfer scheme that maximizes political support for a given tax). A full investigation of this question is beyond the scope of his paper, as it requires a new model of political opinion and policymaking. But, a few points in this direction are worth making by way of conclusion.

Political targeting: First, note that a targeting scheme is well suited to the task of neutralizing political blocks. Where a targeting scheme is based on predicted damages, the inclusion of any variable in the targeting equation would ensure that consumers with that characteristic are not losers on average. Thus, to the extent that a group of voters or stakeholders are deemed critical to the political survival of a policy, putting that variable into the transfer prediction equation immediately creates a balance between winners and losers.

Perhaps the most obvious example is geography. If a transfer function, for example, includes state dummy variables, then winners and losers will not be concentrated among any state. More precisely, the average residual within each state will be zero, so that, for example, no senators would have constituents who lose on average.[10]

Alternative loss functions: If the goal was to minimize the number of losers, a planner

[10]This statement relates to the case where revenue outlay is equal to initial private burden, ignoring the distribution of gains. If gains are concentrated among groups, the prediction equation can be done on estimated net burdens to restore the result.

would begin with a different loss function (neither OLS nor LAD). The LAD loss function is the correct one for checking a necessary condition for a Pareto improvement, but if the true motivation for the exercise is a political economy one, then it might be the case that the planner wishes to limit the number of losers to some politically acceptable number. What loss function could be used that usefully captures the importance of status quo bias?

A loss function that minimizes the number of losers is easy to program mathematically, but it will have impractical properties. For example, a loser minimizing program would likely take the richest person in the sample and take all of their money in the form of a negative lump sum transfer so as to enhance the budget available for others. Some other restrictions on the loss function are needed to make political sense of this problem.

As a suggestive next step, however, I explore two alternative loss functions and show how optimizing against them changes the final distribution of burdens, as compared to OLS as a benchmark. One way of capturing the notion of a desire to minimize losses, as opposed to simply accurately predict damages, is to introduce an asymmetry in the loss function. For example, a planner might not care at all about winners, but instead cares only about minimizing losers, but with a quadratic loss function for losses. Mathematically, this example is expressed with the following objective function, where the revenue constraint is included:

$$\min_T \sum_i \min(0, c_i - T(\mathbf{X}_i))^2 \quad \text{s.t.} \quad \sum_i T(\mathbf{X}_i) \leq \sum_i c_i = R \tag{1}$$

The optimal linear in parameters transfer function for expression 1 can be solved numerically. Note that even though the objective function does not value minimizing gains, the budget constraint implies a penalty for gains, so the results may not differ dramatically from OLS. Preliminary numerical results are displayed in Figure 4 which plots the distribution of net gains for two policies that satisfy the same revenue constraint and target based on the same set of covariates (those used in column C, table 3). The green histogram represents the distribution of net losses produced by OLS, where the white histogram represents the distribution of net losses from the asymmetric loss function.

The differences are subtle. The asymmetric loss function somewhat reduces the right tail (the most extreme losers), and has a less peaked distribution. Even so, a regression of one set of residuals on the other produces an R^2 of 0.95 with a slope very close to one, suggesting that differences in the final outcome are small.

A second way of modifying the loss function to care more about losers is to change the exponent on the loss function. It is well understood that median regression is less sensitive to outliers than is OLS. Here, we might be interested in being *more* sensitive to outliers, so

Figure 4: Distribution of Net Losses for Symmetric and Asymmetric Loss Functions

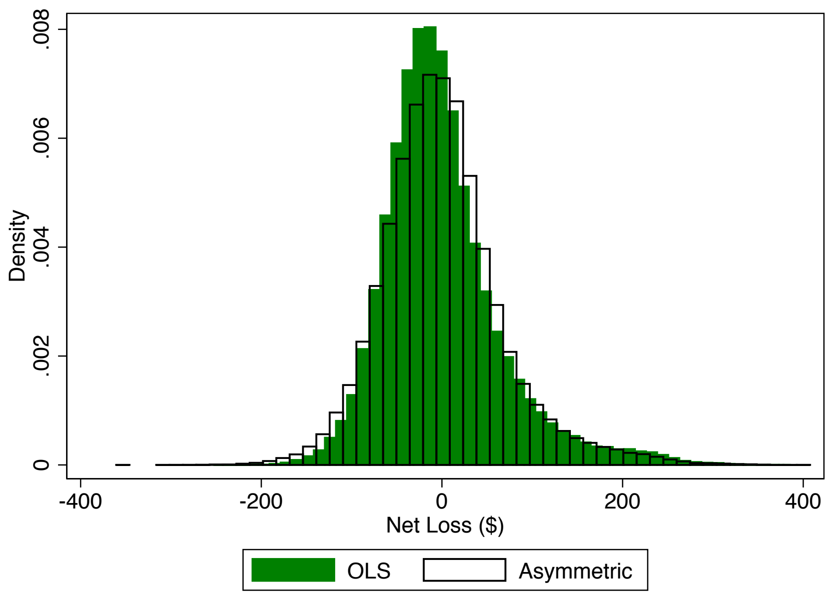

Figure shows distribution of net losses (positive vales) and gains (negative values) for baseline symmetric loss function (OLS), and for the asymmetric loss function in expression 1. Targeting is based on same covariates that are included in column C, table 3.

that the transfer scheme is skewed more towards attempting to "reach" the biggest losers.

A parsimonious way to capture this idea is to specify a class of objective functions that minimize the absolute value of residuals raised to a power, denoted ρ:

$$\min_T \sum_i |c_i - T(\mathbf{X}_i)|^\rho \quad \text{s.t.} \;\; \sum_i T(\mathbf{X}_i) \leq \sum_i c_i = R \tag{2}$$

This loss function nests OLS ($\rho = 2$) and median regression ($\rho = 1$). When $\rho > 2$, the loss function will put more weight on reducing the extreme outcomes, as compared to OLS.

To explore the sensitivity of final outcomes to this alternative objective function, I estimate a series of regressions for values of ρ ranging from 1 to 4, using a common set of covariates (those used in column C of table 3). As in the case of the asymmetric loss function, the distribution of net losses that emerges from preliminary numerical optimization differs only modestly across specifications. The distribution of losses is right skewed, and the most notable change across specifications is in the right tail (the biggest losers).

Figure 5 summarizes the impact on the right tail of the distribution by plotting the 90th, 95th and 99th percentiles of the net loss distribution, along with the skewness of the net

Figure 5: Distributional Statistics Among Losers with Different Loss Function Exponents (ρ)

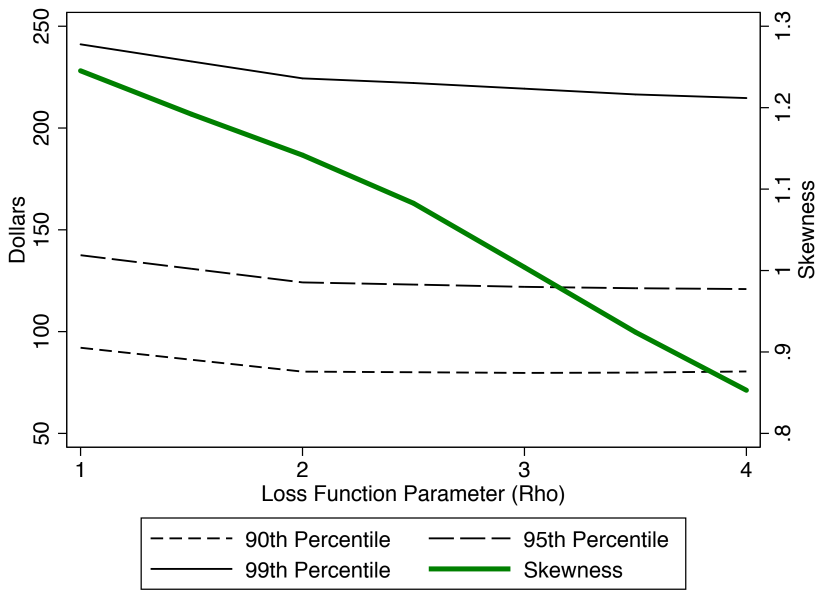

Figure shows percentiles characterizing the distribution of losers and skewness, as a function of the exponent on the loss function from expression 2. Targeting is based on same covariates that are included in column C, table 3.

loss distribution, as a function of ρ. These extreme data points decline as ρ increases, as expected, though the differences do not seem dramatic from an economic standpoint.

In brief, preliminary exploration of two alternative loss functions show the potential to think about optimizing the transfer scheme according to alternative criteria. They also, however, suggest that differences in final distribution may be small. The magnitude differences are due in part to the limited ability of the available covariates to predict consumption losses. Intuitively, with better predictability, the distribution of optimal net losses should differ more across specifications.

Political economy may depend on the concentration of winners and well as losers. Here I think about focusing on the losers as an initial exploration. The logic of collective action suggests that a politically optimal allocation might involve diffuse losses among the majority, combined with a concentration of gains among a few who would be motivated to mobilize. Thus, I believe that the next step in this research is to merge some of the issues raised here with insights from political economy models and cooperative game theory that attempt to capture different criteria that make policies acceptable to a group. Note that the key insight about prediction will carry forward—regardless of the planner's objective function, the ability to accurately predict burdens with variables in the transfer function will determine the level of control the planner enjoys over the final distribution of net burdens.

6 Conclusion

This paper uses theory and data to argue that policies like Pigouvian taxes—which improve social efficiency but create heterogeneous costs and benefits—will inevitably create some losers because transfers targeting the losers will tend to be imprecise.

The theory demonstrates how one's ability to compensate losers depends on the predictability of heterogeneous policy burdens and the size of efficiency gains. The theory delivers a specific test that can be taken directly to data. Empirically, the case of a gasoline tax is considered, and the possibility of a Pareto improvement is soundly rejected. Preliminary evidence on other externality creating goods suggests the same conclusion. In short, Pigouvian taxes create losers.

This is an important conclusion as it suggests the need for nuance in a range of important policy debates. Economists sometimes argue that efficiency-enhancing policies, at least in principle, can be paired with targeted transfers so as to rationalize completely abstracting from distributional implications and judging policies purely on efficiency grounds. This paper argues for more caution in this line of reasoning. The fact that a policy creates losers is not in and of itself a reason to reject the policy, but it does point to why efficiency enhancing policies may not prevail in the policy-making process.

It is worth stating again that a concern with compensating losers is not born from the objective of maximizing social welfare. Standard social welfare maximization does not give any special status to the status quo allocation, and gains and losses per se are irrelevant. The informal motivation of this paper and its concern with compensating losers is about the political process. Pockets of losers who are particularly harmed by a policy may organize to obstruct it. If one takes the view that efficiency-enhancing policies are in fact desirable, then the fact that not all losers can be compensated should shift attention to the question of how many losers must be compensated, and by how much, in order to enable an efficient policy to prevail.

The final portion of the paper is intended as a first step in that direction. It demonstrates the value of targeting in compressing the distribution of winners and losers as a function of total revenue expended, and it experiments with alternative objective functions that aim to prevent especially large losses from occurring. A deeper explanation of these alternative targeting plans could further aid in the constructive design of policy packages that preserve economic efficiency while satisfying political constraints generated by distributions of burdens.

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A Appendix: Proofs

Condition 1. *Let c_i be the private surplus losses from a marginal tax, N be the number of agents, $T(\mathbf{X}_i)$ be a transfer scheme that recycles all of the revenue from the tax, and g_i be the externality gains, where $g_i \geq 0\ \forall i$. A Pareto improvement is not possible if the average absolute errors exceed twice the average surplus gain; i.e., a Pareto improvement is not possible if*

$$\frac{1}{N}\sum_i |c_i - T(\mathbf{X}_i)| \geq \frac{2}{N}\sum_i g_i.$$

By Roy's identity, for the marginal tax, total revenue raised is equal to the lost surplus, so $R = \sum_i c_i$. For a transfer scheme that uses up all of the revenue, it must be the case that $\sum_i T(\mathbf{X}_i) = R = \sum_i c_i$. Therefore, for any such transfer scheme, it must be the case that errors (the difference between transfers and costs) are zero on average: $\sum_i (c_i - T(\mathbf{X}_i)) = 0$.

Unless all errors are exactly zero, there must be both losers (for whom $c_i - T(\mathbf{X}_i) > 0$) and winners (for whom $c_i - T(\mathbf{X}_i) \leq 0$). Denote the set of losers as $i \in L$ and the number of losers as N_L, and denote the set of winners by $i \in H$ and the number of winners as N_H, with $N_L + N_H = N$.

Because the sum of all errors is zero, it must be the case that the sum of errors for all winners is exactly the opposite of the sum of all errors for losers. Denote this sum as Z:

$$-\sum_{i\in L}(c_i - T(\mathbf{X}_i)) = \sum_{i\in H}(c_i - T(\mathbf{X}_i)) = Z.$$

Denote the average absolute error by $|\bar{\epsilon}|$, with $|\bar{\epsilon_L}|$ and $|\bar{\epsilon_W}|$ representing the average absolute error of losers and winners respectively. The average absolute error of both winners and losers can be found with reference to Z by writing the weighted average of absolute errors among winners and losers. Because all errors are positive (negative) among losers (winners), the average absolute errors are simply the absolute value of the average errors for each group:

$$|\bar{\epsilon_L}| = \sum_{i\in L}|c_i - T(\mathbf{X}_i)| = \frac{Z}{N_L} \quad \text{and} \quad |\bar{\epsilon_H}| = \sum_{i\in H}|c_i - T(\mathbf{X}_i)| = \frac{Z}{N_H}.$$

The average absolute error for all observations is the weighted average of the two groups, which by substitution is just $2Z/N$:

$$|\bar{\epsilon}| = \frac{N_L|\bar{\epsilon_L}| + N_H|\bar{\epsilon_H}|}{N_L + N_H} = \frac{2Z}{N}$$

Z represents the total loss of all losers. A Pareto improvement is possible only if the surplus gains g_i are distributed so as to offset all of the losses. Thus, a Pareto improvement is only possible if the total surplus G exceeds Z. This is equivalent to saying that the average absolute error must be less than two times the average surplus gain. □

B Appendix: Data comparisons

The CEX was chosen as the primary data source for this analysis because it includes a rich set of demographic covariates and a measure of gasoline expenditures, and because it is the standard data source in the most closely related literature. Gasoline expenditures, however, are based on self-reports and may be subject to mismeasurement. If there is a lot of noise in the expenditure data, this will make prediction more difficult. This section attempts to establish some sense of the reliability of CEX data by comparison to other surveys.

Of course, at the very highest level, problems of measurement do not challenge the key thesis of this paper. Instead, these problems reinforce it. If the best available data on expenditures are noisy measures of true burdens, it only makes it more difficult to design an accurate targeting scheme and thereby to compensate losers.

The National Household Travel Survey

An alternative measure of motor fuel consumption can be taken from the National Household Travel Survey, which is a nationally representative survey performed most recently in 2001, 2009 and 2017. That survey gathers a measure of annual vehicle miles traveled and then divides by the EPA estimated fuel economy of a vehicle to arrive at an estimate of annual fuel consumed. This is multiplied by average gasoline prices from the Energy Information Administration to impute expenditures. In contrast, the CEX asks consumers directly about expenditures.

The 2009 version of the NHTS is the most recent survey in which the miles traveled variable was based on two odometer readings (the survey respondent is asked to look at their odometer), rather than a retrospective self report. I compare the motor fuels expenditure data from that survey to the CEX from 2009. Figure 7 shows that fuel expenditure distribution from the two surveys for different samples. The top panel shows all households. This shows that the NHTS has higher expenditures on average, with a substantially longer right tail.

In part this may be due to differences in unit definitions across the two surveys, as the CEX is broken into smaller consumer units than the household definition used in the NHTS. Differences persist, however, when comparing households with the same number of members. The bottom two panels of Figure 7 compare households with one vehicle (on the left) and with two vehicles (on the right). In particular for the one vehicle households, the distributions do fit better. Nevertheless, the two data sources do show non-trivial differences in this fundamental measure.

Though there are some advantages to the measure of fuel expenditure in the NHTS, it has the disadvantages of requiring imputation of fuel economy and gasoline prices. Gasoline prices vary significantly across locations and time. Fuel economy varies substantially with where a vehicle is driven. Thus, it is not obvious which survey measure is more reliable. Regardless, the fact that there are substantial differences suggests that mismeasurement could be important.

Ultimately for the purposes of this paper, what matters is predictability. To compare predictability across the surveys I identify a set of demographic variables that appear to be defined consistently in both surveys: income, Census region, an urban indicator, family size

Figure 6: Comparison of Distribution of Implied Fuel Expenditure in CEX and NHTS

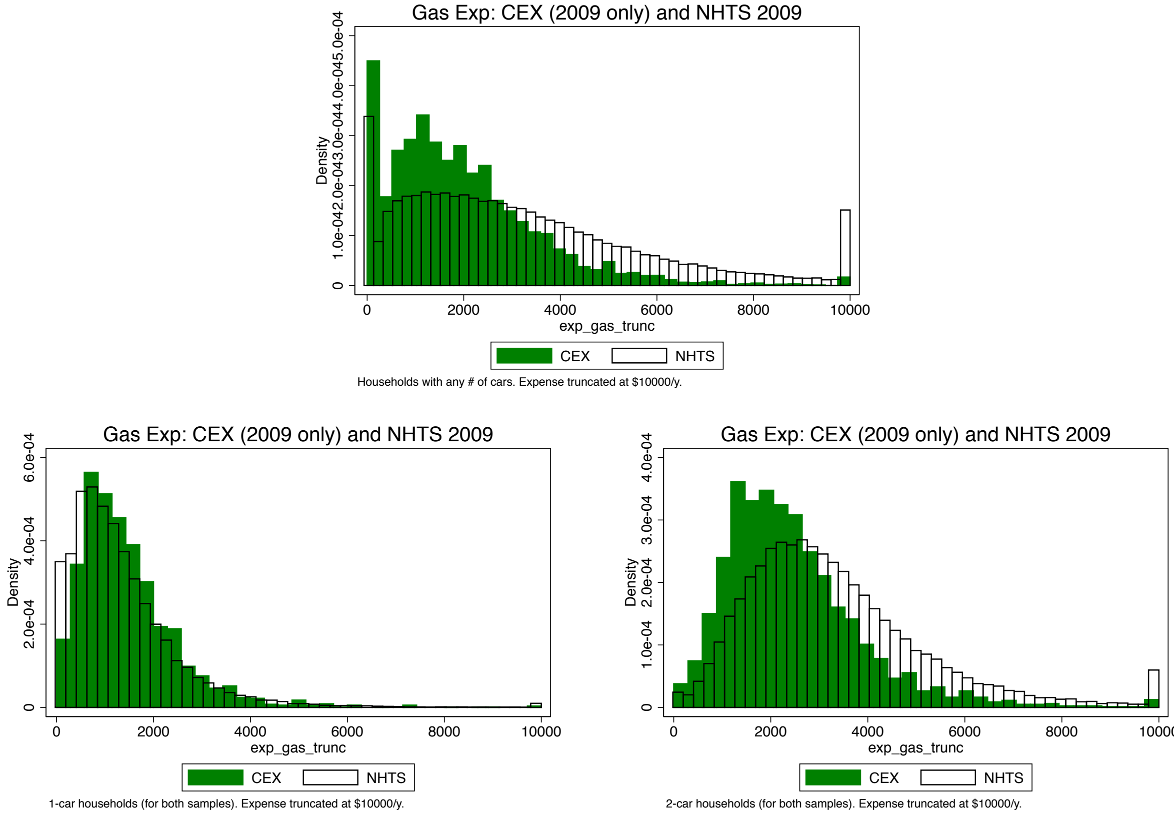

Figure shows histogram of estimated annual fuel expenditure by households using CEX and NHTS data. Left panel is for households with one vehicle. Right panel is for households with two vehicles. Both are from 2009 surveys. All distributions are truncated at $10,000 of annual expenditure.

and number of persons over 18. Table 8 reports the R^2 for parallel regressions of gasoline expenditures on these controls, varying the set of controls and whether the regressions using sample weights.

For the base set of controls, the CEX and NHTS show very levels of predictability as summarized by the R^2. This is true regardless of weighting. In additional specifications (not shown), the results change very little when using dummies for the household size variables or adding state dummies instead of Census regions. The one difference that did emerge in a specification search was that the total number of vehicles owned by the household has a stronger explanatory power in the NHTS, and in particular when weighting, this variable notably increases prediction accuracy. The NHTS collects mileage information (from which expenditures are imputed) for each car, ensuring a mechanical connection. Table 8 reports the weighted and unweighted versions of these regressions showing the greater impact of vehicle controls in the NHTS.

Overall, the comparison of the CEX with the NHTS suggests that there are some notable differences in estimated gasoline expenditure, though in most cases there is not a large difference in predictability within the two samples. While mismeasured expenditures in the

Table 8: Predictability of Gasoline Expenditures in CEX versus NHTS

	CEX	NHTS	CEX	NHTS	CEX	NHTS	CEX	NHTS
R^2	.278	.232	.250	.267	.359	.380	.322	.431
Base controls	Y	Y	Y	Y	Y	Y	Y	Y
Number of vehicles	N	N	N	N	Y	Y	Y	Y
Weighted	N	N	Y	Y	N	N	Y	Y
N	9,116	137,938	9,116	137,938	9,116	137,938	9,116	137,938

Table compares 2009 CEX to 2009 NHTS. Dependent variable is annualized gasoline expenditures. Base controls include income, Census regions, urban dummy, family size and number of persons over 18. The additional variable is total number of vehicles in the household.

CEX may imply that the R^2 is artificially low as compared to some theoretical baseline, it is worth emphasizing a final time that trouble measuring consumption (and hence the burden of a tax) actually makes targeting transfers accurately more difficult.

The Residential Energy Consumption Survey

This paper focuses on gasoline taxes, but it also briefly presents results on home energy consumption. The data quality of the home energy consumption variables in the CEX can be explored by comparison with the Residential Energy Consumption Survey (RECS), which is most recently available in 2009 and 2015. The RECS has the key advantage that electricity and natural gas expenditures are validated against billing records, so the data quality are much better for those variables than in most surveys.

Figure 7 shows the distribution of electricity and natural gas expenditures in the CEX and RECS, pooled for 2009 and 2015. Overall, the similarity in the distributions is broadly encouraging, but there are differences. The CEX shows more observations with low consumption, especially for gas. It also has a longer right tail. This may be in part because the CEX consumer units are on average smaller, but it may also be evidence of mismeasurement.

The primary concern with mismeasurement for the core purposes of this study is that it might artificially deflate the degree of predictability. Table 9 shows the R^2 from regressions with the overlapping common set of covariates between the RECS and CEX. The RECS does show a somewhat higher R^2. The data are not winsorized in these regressions. In other specifications (not shown), truncating the right tail of the distribution for high values has little effect on the R^2. Again, the high level point that consumption will be hard to measure and predict is reinforced if the CEX has measurement problems, though it certainly opens the possibility of using better measured surveys to design the transfer system.

Figure 7: Comparison of Distribution of Implied Electricity and Natural Gas Expenditures in CEX and RECS

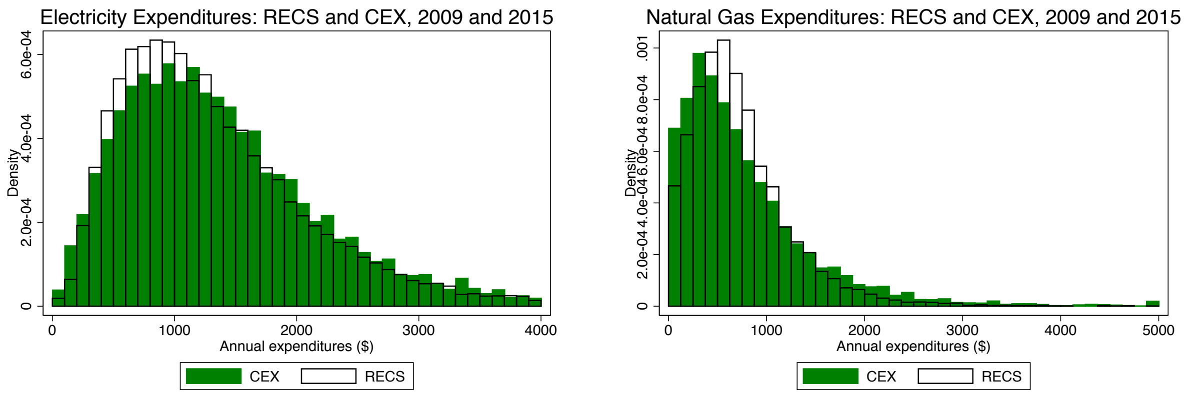

Figure shows histogram of estimated annual fuel expenditure by households using CEX and NHTS data. Left panel is for households with one vehicle. Right panel is for households with two vehicles. Both are from 2009 surveys.

Table 9: Predictability of Home Energy Expenditures in CEX versus NHTS

	Electricity				Natural Gas			
	CEX	RECS	CEX	RECS	CEX	RECS	CEX	RECS
R^2	.198	.262	.180	.263	.123	.218	.114	.178
Base controls	Y	Y	Y	Y	Y	Y	Y	Y
Weighted	N	N	Y	Y	N	N	Y	Y
N	17,802	17,769	17,802	17,769	11,263	10,798	11,263	10,798

Table compares 2009 and 2015 CEX to 2009 and 2015 RECS. Dependent variable is annualized expenditures on electricity or natural gas. Base controls include income, Census regions, urban dummy, family size and number of persons over 18. Samples are restricted to households with positive expenditures for natural gas.