Charitable Giving and Federal Income Tax Policy:  
Additional Evidence based on Panel-Data Elasticity Estimates  

by  

Kevin Stanton Barrett  

Dissertation submitted to the Faculty of the  
Virginia Polytechnic Institute and State University  
in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in General Business  
(Accounting)  

APPROVED:  

Cherie J. O'Neil, Chair  
Accounting  

Robert M. Brown  
Accounting  

James A. Yardley  
Accounting  

Anya M. McGuirk  
Agricultural Economics  

Richard Steinberg  
Economics  

G. Rodney Thompson  
Finance  

August 12, 1991  
Blackburg, Virginia
Charitable Giving and Federal Income Tax Policy:
Additional Evidence based on Panel-Data Elasticity Estimates
by
Kevin Stanton Barrett
Cherie J. O'Neil, Chairperson
Accounting
(ABSTRACT)

Nearly all traditional charitable-giving studies conclude donors are more responsive to price-reducing charitable deductions (the price effect) than they are to income-reducing tax payments (the income effect). Thus, taxes stimulate giving. In addition, this empirical evidence also indicates that the charitable deduction is treasury efficient. This traditional understanding was recently challenged by studies employing observations on the same individuals across time (panel data). These panel studies provide evidence which suggest that donors are either much more responsive to income-reducing tax payments than they are to price-reducing charitable deductions or just as responsive to both. Further, price elasticity estimates are much greater than negative one. Thus, the deduction is inefficient and giving is either neutral to, or inhibited by, taxes.

By using a methodology which combines the best aspects of prior panel studies, a richer utilization of consumer

Abstract
theory, and formal tests of statistical and specification adequacy, a dynamic model of giving is found that dominates its rivals on statistical, specification, and a priori theoretical grounds. Taken together, the short-run efficiency and neutrality findings generated by this dynamic model of giving indicate that the deduction is an efficient means for stimulating giving. This means that traditional estimates are probably capturing donors' short-run response to changes in price and income. In contrast, long-run results suggest that the deduction neutralizes donors' response to changes in marginal tax rates and is treasury inefficient. Besides providing a harmonizing link to the traditional literature, these findings provide an interesting contrast to those reported in prior panel studies and underscore the importance of reexamining model specification and estimation.

Abstract
ACKNOWLEDGEMENTS

I would like to thank my committee members for their timely contributions throughout this study, Indiana University's Center on Philanthropy for its generous funding, and the participants of the American Tax Association's doctoral research colloquium, Indiana University Center on Philanthropy's Seminars in Nonprofit Governance, and the National Tax Association Spring Symposium for their helpful comments.

This work is dedicated to my father, Stanton Stuart Barrett.
# Table of Contents

1.0 Statement of the Problem. ........................................... 1

1.1 Introduction. ......................................................... 1

1.2 Background. .......................................................... 2

1.2.1 Modeling donors’ giving: An economic perspective. .... 2

1.2.2 Unveiling the theory. ............................................. 6

1.2.3 The traditional empirical understanding. ................. 11

1.2.4 New Results. ....................................................... 15

1.2.4.1 The panel-data analysis environment. ................. 15

1.2.4.2 Ground-breaking panel-data results. ................... 19

1.3 Statement of the Problem. .......................................... 21

1.4 Research Questions. ................................................ 21

1.5 Research Design. .................................................... 22

1.6 Findings. .............................................................. 27

1.7 Overview of the Dissertation. .................................... 30

2.0 Review of the Literature. .......................................... 31

2.1 Clotfelter. ........................................................... 31

2.2 Broman. ............................................................... 37

2.3 Daniel. ............................................................... 43

2.4 Frischmann and Lin. ............................................... 46

2.5 Barrett. ............................................................... 48

2.6 Summarizing the Panel-Data Literature. ..................... 52

2.7 Extending the Panel-Data Literature. ......................... 57

Table of Contents
LIST OF TABLES

Table 1.1. Summary of the Refutable Propositions Motivated by a Dynamic Version of Consumer Theory. .......................... 12
Table 1.2. Income and Price Elasticities from Broman and Daniel's Ground-Breaking Studies. .......... 20
Table 2.1. A Summary of the Elasticity Estimates Reported by Clotfelter and Broman. .............. 53
Table 2.2. A Summary of the Elasticity Estimates Reported by Daniel, Frischmann and Lin, and Barrett. ......................... 55
Table 3.1. Descriptive Statistics for Adjusted Gross Income, Disposable Income, and Price. .... 81
Table 3.2. Descriptive Statistics for Charitable Contributions, Marital Status, Age, and Dependents. .............................. 83
Table 4.1. The Dynamic Two-Way Fixed-Effects Model: Parameter Estimates and Correlation Coefficients. ......................... 101
Table 4.2. A Summary of the Research Hypotheses. ....... 103
Table A.1. Results of Tests Evaluating the Statistical Adequacy of Static Models of Giving. ........ 149
Table A.2. Results of Tests Evaluating the Statistical Adequacy of Dynamic Models of Giving. .......... 151
Table A.3. A Ranking of Charitable Giving Models Based on Overall Level of Statistical Adequacy. .... 153
Table B.1. Analysis of Static Models of Giving. ......... 171
Table B.2. Analysis of Dynamic Models of Giving. ....... 173

List of Tables
LIST OF ILLUSTRATIONS

Figure 1.1. A Sketch of the Research Design. ............... 23

Figure 3.1. Panel Sample Configuration. ....................... 78

Figure A.1. A Sketch of Spanos's Methodology. ............. 130

Figure A.2. Assessing Statistical Adequacy. ................. 135

Figure A.3. Normal Probability Plot of Raw Residuals from the Dynamic Two-Way Fixed-Effects Model. ....................... 157

Figure A.4. Histogram of the Raw Residuals Generated from the Dynamic Two-Way Fixed-Effects Model. ....................... 157

Figure A.5. Normal Probability Plot of the Standardized Residuals from the Dynamic Two-Way Fixed-Effects Model. ....................... 159

Figure A.6. Histogram of the Standardized Residuals from the Dynamic Two-Way Fixed-Effects Model. ....................... 159

Figure A.7. A Plot of Raw Residuals on Charitable Giving. ............... 161

Figure B.1. Assessing Specification Adequacy. .............. 165

Figure B.2. Identifying the 'Best' Panel-Data Model. ....167
1.0 STATEMENT OF THE PROBLEM

1.1 Introduction.

Nonprofit organizations\(^1\) compose a unique and important sector of the U.S. economy. These organizations provide goods and services which mitigate government and market failures in the public and for-profit sectors [Weisbrod (1977) and Hansmann (1980)]. Achievement of the respective missions of these organizations depends largely upon the ability of nonprofit managers to procure financial resources. Charitable giving provides roughly 40% of the total financial resources available to the nonprofit sector. Gifts made by individuals account for about 80% of all charitable giving [Clotfelter (1989)].\(^2\) Effective governance of nonprofit organizations is

---

\(^1\)Public service organizations and mutual benefit organizations are the two basic types of institutions that have arisen in response to governmental and market failures. Public service organizations are primarily made up of §501(c)(3) organizations such as churches, hospitals, charities, and educational and scientific institutions. These entities have been granted a tax-exempt status and can offer a charitable deduction to their itemizing donors. In contrast, mutual benefit organizations, such as clubs, unions, and other associations, which exist primarily for the benefit of their members, enjoy only the tax-exempt status. The focus of this study is restricted to public service organizations.

\(^2\)This statement implicitly acknowledges that charitable giving is broader than individual giving. However, the scope of this work is restricted to individual giving.

Statement of the Problem
facilitated when management improves its understanding of donors' giving impulse.

1.2 Background.

1.2.1 Modeling donors' giving: An economic perspective.

Nearly all studies composing the charitable-giving literature use a restricted version of consumer theory as a framework for examining how the government's taxation decisions influence donors' giving behavior [e.g., Varian (1987a, 1987b)].\(^3\) Within this framework, taxes influence giving in two ways. Price-reducing charitable deductions stimulate giving, ceteris paribus.\(^4\) This is the price effect. Income-reducing tax payments inhibit giving. This is the income effect. The opposing nature of these effects betrays taxation's analytically ambiguous impact on donors' giving.

---

\(^3\)Charitable giving is a multifaceted phenomenon and lends itself to many valid research methodologies. When an analysis is restricted to a particular theoretical framework, important cause and effect relationships may be overlooked. Piecemeal advances, however, are often a necessity until methodologies are joined by theoretical and empirical advances.

\(^4\)The charitable deduction is one of several itemized deductions that the Internal Revenue Service allows taxpayers to use in reducing their taxable income. This implies that donors' last-dollar price of giving is equal to one minus the tax paid on their last dollar of income (marginal tax). For example, if you itemize and your marginal tax rate is 28%, the price of your $1.00 gift is $0.72 because this gift reduces your tax liability by $0.28.
By implication, policy researchers must appeal to the empirical realm to determine whether donors are more responsive to price-reducing charitable deductions or income-reducing tax payments.

Income and price elasticities, two parameters of the demand function, are useful in empirically assessing donors' response to taxes. The income elasticity measures the percentage change in giving induced by a one-percent increase in disposable income, ceteris paribus. Because tax payments inhibit giving by reducing donors' disposable income, empirical estimates of this elasticity should have a positive sign. The price elasticity measures the percentage change in giving induced by a one-percent increase in price. Because the deduction stimulates giving by reducing its price, empirical estimates of this elasticity should have a negative sign.

The charitable deduction can be viewed as a "tax expenditure", that is, as a sacrifice of otherwise collectible tax dollars in order to stimulate private expenditures on services which would otherwise be publicly funded. Feldstein [1980] argues that tax expenditures in the form of charitable

---

5 The term taxes is used loosely to refer to donors' relative responsiveness to price-reducing charitable deductions and income-reducing tax payments.

Statement of the Problem
deductions are justified when private expenditures are price elastic. When donations are price elastic, the flow of resources into the nonprofit sector more than offsets the loss of government revenue. Estimates reported below test for...

This paragraph greatly oversimplifies the highly debated question of why a charitable deduction should exist [see Gergen (1988) for an excellent discussion of the debate surrounding this question]. Many economists are able to justify the availability of the charitable deduction regardless of the price elasticity's magnitude. For example, Weisbrod (1986) and Hochman and Rodgers (1977) present subsidy arguments to this end. Weisbrod believes private charity responds better to diversity in demand for public goods than the government does. Thus, a charitable giving subsidy is probably the only way a high-preference minority can obtain a particular public good at the level they desire when facing an indifferent majority. Hochman and Rodgers believe a charitable deduction pushes the funding of a public good closer to an optimal level by shifting part of the cost to freeriders. The shifting takes place when freeriders are forced to support tax-exempt activities by foregoing public goods they could have received had the government's revenue not been reduced by allowing the charitable deduction. In these subsidy cases, the price elasticity simply indicates to what extent the redistributive effect of a tax is amplified by the charitable deduction.

Andrews’s (1972) believes that the charitable contribution should be allowed because it is consistent with the objective of the income tax. More specifically, charitable giving diverts economic resources from personal consumption and wealth accretion to public consumption. If these resources are not available for personal consumption and wealth accretion, they do not constitute income and therefore should not be taxed. The charitable deduction makes this tax-exempt treatment possible, at least for itemizing taxpayers.

Finally, Bittker (1972) presents equity arguments to justify the allowance of the charitable deduction. He believes individuals who make charitable contributions are made less well-off and consequently should pay less tax than other individuals who spend their resources on personal consumption. The charitable deduction reduces donors’ taxable income, thus allowing for the reduction in their well-being. In these last two cases, the price elasticity would merely indicate how willing itemizing taxpayers are to subject themselves to decrements in their economic resources.

If donations are price elastic (i.e., for purposes of this study, the price elasticity is considered to be elastic if it is less than or equal to negative one), a deduction for giving is superior to direct

Statement of the Problem
this treasury efficiency.

When testing for treasury efficiency, one is comparing two tax regimes that both collect the same revenue - one with deductibility and one without deductibility. This is quite a different comparison than one typically faces in tax reform. More commonly, marginal tax rates are adjusted without making compensating changes that hold total tax collections constant, and it is of great interest to analyze the effect of such changes on giving. Giving is said to be 'neutral' when a change in marginal tax rates causes no net change in giving.

It is also possible to test for neutrality. The percentage change in donations induced by a tax-rate change is equal to the price elasticity times the percentage change in price plus the income elasticity times the percentage change in after-tax income. Because a tax-rate change results in percentage changes in price and income that are numerically equal, neutrality occurs when income and price elasticities are equal in magnitude and opposite in sign.\(^8\)

Please note that it is possible for giving to be both neutral and treasury efficient. This occurs when both the government expenditures. This does not imply that a deduction is the optimal way to stimulate expenditures. For example, a deduction extended only to donations in excess of some floor may be more efficient.

\(^8\) See footnote 10 (page 8) for a discussion of the thought experiment that motivates the conclusion supporting this argument.

Statement of the Problem

5
income and price elasticities are substantial. Intuitively, when we extend deductible status to donations, we are making a price change with no inherent accompanying income change; when we change tax rates, both price and after-tax income move in tandem.

1.2.2. Unveiling the theory.

The restricted version of consumer theory permeating this literature has a noteworthy deficiency. Giving is portrayed as a 'static' activity. This year's gifts are modeled as though they are made independent of donors' habit persistence tendencies and last year's and next year's prices and disposable incomes. This restrictive assumption is easily relaxed when consumer theory's habit persistence and life cycle arguments are considered [e.g., Clotfelter (1980) and Watson (1985)]. These arguments reveal that in addition to this year's price and income elasticities, consumer theory motivates 'new' elasticities which account for the ways in which giving is influenced by donors' habit persistence, last year's price and income, and next year's price and income. This implies that the restricted or static version of consumer theory is a special case of a more general or dynamic theory of giving. Thus, in this new setting, giving can be portrayed as a 'dynamic' activity. The 'new' elasticities that result have the following expected signs:

Statement of the Problem
1. According to the habit persistence argument, donors' learning about tax changes takes place with some delay. Consequently, factors that shaped last giving patterns continue to exert some residual influence on this year's giving. Thus, this year's gifts are positively related to last year's gifts [e.g., Pilivan, Evans, and Callero (1984)].

2. Increases in transient income are not 'rationally' spent in the year of occurrence. Rather, consumption of each good, including giving, is smoothed. Consequently, this year's gifts are positively related to last year's income.

3. Donors who faced a relatively higher price of giving last year are more likely to shift a portion of their intended gifts into 'this' year. Thus, this year's gifts are positively related to last year's price.

4. Donors smooth a portion of the potential consumption associated with anticipated increases in next year's disposable income into 'this' year. Thus, this year's contributions are positively related to next year's income.

5. Donors respond to anticipated increases in next year's price by shifting a portion of next year's intended gifts into 'this' year. Consequently, this year's gifts are positively related to next year's price.

These expectations suggest that empirical estimates of these elasticities should have positive signs.

Assessing efficiency and neutrality in a dynamic setting is of great interest. This year's price elasticity is used to determine whether the deduction achieves short-run efficiency. If this year's price elasticity is less than or

---

As noted in the discussion below, panel-data estimation techniques control for factors having a definite but constant impact upon giving. Because permanent income and price are by definition constant, the

Statement of the Problem 7
equal to negative one, the deduction is efficient in the short-run. One may expand the analysis of efficiency to include last year's, this year's, and next year's price elasticities. The sum of these elasticities represents donors' long-run response to transitory changes in price.\textsuperscript{10}

influence they exert on this year's giving is included in donor-specific constants. Consequently, price and income elasticities must be capturing donors' response to transitory changes in income and price. When taken in isolation (i.e., last year's and next year's price elasticities are held constant), this year's price elasticity tends to have more of short-run orientation.

\textsuperscript{10}The following thought experiment should help to clarify this argument. Suppose the world is composed of two states, tax regime one and tax regime two. These tax regimes have always existed and will continue to do so. Tax regime one differs from tax regime two in only one way, the marginal tax rate is 30 rather than 50 percent. Now, suppose at some point in the middle of time, a taxpayer is changed from tax regime one to tax regime two. If giving is a dynamic activity, this taxpayer will experience simultaneous changes in this year's, last year's and next year's prices. Because our functional form says change in contributions is linearly additive in percentage changes, when changes in disposable income are held constant, the total price-induced percentage change in contributions is obtained as follows:**

\[\%\delta C \equiv (\epsilon_{P-1} \times (\%\delta P_{-1})) + (\epsilon_{P0} \times (\%\delta P_{0})) + (\epsilon_{P+1} \times (\%\delta P_{+1}))\]

The notation \%\delta represents percentage change. Thus, \%\delta C, \%\delta_{P-1}, \%\delta_{P0}, \%\delta_{P+1} represents the percentage change in contributions, last year's price, this year's price, and next year's price, respectively. The Greek letter \epsilon represents elasticity. Thus, \epsilon_{P-1}, \epsilon_{P0} and \epsilon_{P+1} represents last year's, this year's, and next year's price elasticities, respectively.

Since both tax regimes are in a steady state, the percentage change in last year's, this year's, and next year's price is the same. Thus, the total price-induced percentage change may now be expressed as:

\[\%\delta C \equiv (\%\delta^*_{P})(\epsilon_{P-1} + \epsilon_{P0} + \epsilon_{P+1})\]

The notation \%\delta^*_{P} represents the common percentage change in last year's, this year's, and next year's prices.

Because each price undergoes a common percentage change, donors' long-run

Statement of the Problem
response to transitory changes in price (i.e., long-run treasury efficiency) can be assessed by summing across last year’s, this year’s, and next year’s price elasticities. Similar arguments hold for assessing donors’ long-run response to transitory changes in disposable income.

In order to address neutrality, we must say something about the joint effect of changes in price and disposable income on changes in contributions. This expression accommodates this neutrality setting:

\[
\%\delta C = (\%\delta P^*) (\varepsilon_{P-1} + \varepsilon_{P0} + \varepsilon_{P+1}) + (\%\delta Y^*) (\varepsilon_{Y-1} + \varepsilon_{Y0} + \varepsilon_{Y+1})
\]

The notation \%\delta Y represents the common percentage change in last year’s, this year’s, and next year’s disposable income. Recalling that price is equal to \((1 - t_i)\), where the subscript \(i\) represents the marginal tax from either tax regime one or regime two, the change from tax regime one to tax regime two results in the following common percentage change in price:

\[
(\%\delta P^*) = \frac{(1 - t_2) - (1 - t_1)}{(1 - t_2) + (1 - t_1)} = \frac{2(t_1 - t_2)}{2 - t_1 - t_2}
\]

The change in tax regimes also results in the following common percentage change in disposable income:

\[
(\%\delta Y^*) = \frac{(1 - t_2)Y_D - (1 - t_1)Y_D}{(1 - t_2)Y_D + (1 - t_1)Y_D} = \frac{2(t_1 - t_2)}{2 - t_1 - t_2}
\]

Because \(Y_D\) can be factored out, the common percentage change in disposable income is equal to the common percentage change in price. Consequently, the percentage change in contributions can now be expressed as:

\[
\%\delta C = (\%\delta^*) ((\varepsilon_{P-1} + \varepsilon_{P0} + \varepsilon_{P+1}) + (\varepsilon_{Y-1} + \varepsilon_{Y0} + \varepsilon_{Y+1}))
\]

The notation \(%\delta^*\) represents the common percentage change in income and price. This expression implies that the percentage change in contributions is equal to zero either when there is no common percentage change in price and disposable income (which is not the case in this study) or when:

\[
(\varepsilon_{P-1} + \varepsilon_{P0} + \varepsilon_{P+1}) + (\varepsilon_{Y-1} + \varepsilon_{Y0} + \varepsilon_{Y+1}) = 0
\]

That is, the sum of the price and income elasticities equals zero.

**Statement of the Problem**
If this sum is less than or equal to negative one, the
deduction is efficient in the long-run.\textsuperscript{11,12}

Thus, long-run neutrality can be assessed by summing across last year's,
this year's, and next year's price and disposable income elasticities.\textsuperscript{***}
A similar argument holds when assessing short-run neutrality.

\textsuperscript{**}Neither the dynamics of adjustment nor a one-time only change
(with a switch back to the original regime) is explored in this
study. Both of these issues are left for subsequent research.

\textsuperscript{***}The term long-run is used in a relative sense. That is, relative
to this year's price elasticity, the sum of last year's, this
year's, and next year's price elasticities tends to have more of a
long-run orientation.

\textsuperscript{11}Technically, last year's and next year's income and price
elasticity estimates should be restated in terms of net present value.
At issue is how to account for the impact of real and nominal interest
rates on the comparability of intertemporal elasticities. By restating
the appropriate data in terms of 1982 dollars, the influence of nominal
interest rates is mitigated. For the 1979-1986 period covered by this
study's sample, Mehra and Prescott (1985) reveal a real interest rate of
about .8%. Consequently, the real interest rate's influence on elasticity
comparability is inconsequential. To illustrate, suppose last year's and
next year's price elasticities are respectively 0.354 and 0.428. Applying
the appropriate interest factors, the resulting present values are
respectively, 0.357 (0.354 * 1.008) and 0.425 (0.428 / 1.008). Because
the differences are trivial, real interest rates are ignored in the
remainder of this study.

\textsuperscript{12}Within Clotfelter's habit persistence framework, there is an
alternative way of thinking about donors' short- and long-run responses
to taxation-induced changes in price and income [Clotfelter (1980)]. In
this setting, each price and income elasticity estimate represents donors'
short-run response to transitory changes in price and income. By dividing
each of these elasticities by the complement of the elasticity on lagged
giving (1 - the elasticity on lagged giving), one may obtain donors' long-
run response to transitory changes in price and income (see Section 2.1
Clotfelter (page 31) for additional discussion). Thus, the sum of the
long-run price elasticities seems to reflect donors' long-run response to
permanent changes in price. However, as it turns out, this study provides
empirical evidence which suggests that donors respond rapidly to taxation-
induced changes in price and income. Thus, from an interpretational point
of view, Clotfelter's distinction between the short-run and long-run is

\textbf{Statement of the Problem}
This year's price and income elasticities are used to determine whether donors' response to changes in marginal tax rates is neutral in the short-run. If the sum of these elasticities equals zero, changes in marginal tax rates do not cause a net change in charitable giving. Thus, giving is neutral in the short-run. The analysis of neutrality can be expanded to include last year's, this year's, and next year's disposable income and price elasticities. These elasticities are used to determine whether donors response to changes in marginal tax rates are neutral in the long-run. If the sum of these elasticities equals zero, a change in marginal tax rates does not cause a change in charitable giving. Thus, giving is neutral in the long-run.

Table 1.1 summarizes the refutable propositions motivated by this more general or dynamic version of consumer theory. These refutable proposition provide the basis for this study's research hypotheses.

1.2.3 The traditional empirical understanding.

Clotfelter (1985) presents an excellent summary of the traditional learning on taxation's effect on charitable giving. The consensus emerging from this literature has relied upon minor variants of the following traditional model
### Table 1.1 Summary of the Refutable Propositions Motivated by a Dynamic Version of Consumer Theory

**Key:**
- \( C_{-1} \) = Last year's contribution
- \( Y_{-1} \) = Last year's disposable income
- \( P_{-1} \) = Last year's price
- \( Y_0 \) = This year's disposable income
- \( P_0 \) = This year's price
- \( Y_{+1} \) = Next year's disposable income
- \( P_{+1} \) = Next year's price

<table>
<thead>
<tr>
<th>Refutable Propositions</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>The Elasticity Associated With:</strong></td>
<td><strong>Individual Parameters</strong></td>
</tr>
<tr>
<td>( C_{-1} &gt; 0 )</td>
<td><em>Learning about tax changes takes place with a delay. So, last year's giving patterns persist.</em></td>
</tr>
<tr>
<td>( Y_{-1} &gt; 0 )</td>
<td><em>Donors smooth consumption associated with transitory increases in last year's income.</em></td>
</tr>
<tr>
<td>( P_{-1} &gt; 0 )</td>
<td><em>When last year's prices exceed this year's, donors shift some gifts into 'this' year.</em></td>
</tr>
<tr>
<td>( Y_0 &gt; 0 )</td>
<td><em>Part of the smoothing phenomenon, increases in this year's income increase this year's gifts.</em></td>
</tr>
<tr>
<td>( P_0 &lt; 0 )</td>
<td><em>When this year's price exceeds next year's, donors postpone some gifts until next year.</em></td>
</tr>
<tr>
<td>( Y_{+1} &gt; 0 )</td>
<td><em>Donors expecting transitory increases in income smooth some consumption into the current year.</em></td>
</tr>
<tr>
<td>( P_{+1} &gt; 0 )</td>
<td><em>Donors who face higher prices next year shift some of next year's gifts to 'this' year.</em></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_0 \leq -1 )</td>
</tr>
<tr>
<td>( P_{-1} + P_0 + P_{+1} \leq -1 )</td>
</tr>
</tbody>
</table>

**Efficiency**
- The deduction is efficient in the short-run.
- The deduction is efficient in the long-run.

<table>
<thead>
<tr>
<th>Neutrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_0 + Y_0 = 0 )</td>
</tr>
<tr>
<td>( (P_{-1} + P_0 + P_{+1}) + (Y_{-1} + Y_0 + Y_{+1}) = 0 )</td>
</tr>
</tbody>
</table>

**Neutrality**
- Taxes are neutral in the short-run.
- Taxes are neutral in the long-run.
of giving:

\[
\ln \text{Contribution} = \beta_0 + \beta_1 (\ln \text{Disposable Income}) + \\
\beta_2 (\ln \text{Price}) + \beta_3 (\text{Marital Status}) + \\
\beta_4 (\text{Age}) + \beta_5 (\text{Number of Dependents}) + \\
\text{error term}
\] (1)

The natural log (ln) transformation of donors' charitable contribution, disposable income, and price of giving measures enables researchers to interpret \( \beta_1 \) and \( \beta_2 \) as elasticities.\(^{13}\) Reflecting the conventional usage of consumer theory, this model portrays current giving as a static activity and implicitly assumes donor- and time-specific characteristics are uncorrelated with the regressors.

Nearly all of the studies underlying the traditional understanding have utilized either time-series or cross-sectional data to generate income and price elasticity estimates. The resulting traditional price elasticity estimates are almost always less than -1.00 and tend to cluster about -1.30. Corresponding income elasticity estimates are almost always less than 1.00 and tend to cluster

\(^{13}\) Marital status and age are modeled as zero-one dummy variables. To clarify, because tax returns simply indicate whether a donor has taken an old age exemption, there is insufficient information to model age as a continuous variable. The number of dependents is typically modeled as a multichotomous ordinal variable.
about 0.70. These estimates imply that a 10 percent increase in this year's price brings about a 13 percent decrease in charitable giving, ceteris paribus. On the other hand, a 10 percent increase in this year's disposable income brings about a 7 percent increase in charitable giving, ceteris paribus. Because the representative price elasticity, -1.30, more than offsets the representative income elasticity, 0.70, donors are more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. These findings suggest that at a given point in time taxes stimulate charitable giving, ceteris paribus. Further, the representative price elasticity implies that the deduction is efficient. Thus, the deduction is an efficient means of stimulating giving.

These results partially justify the government's current subsidization of itemizers' giving and hint at the desirability of once again extending this subsidization to nonitemizers. They also suggest that multi-period price-increasing tax reform, such as the Economic Recovery Act of 1981 and the Tax Reform Act of 1986, will cause giving to trend downward, ceteris paribus. The resulting reduction implies that managers of nonprofit organizations must think of alternative ways to obtain the financial resources necessary for providing customary levels of goods and services.

Statement of the Problem
1.2.4 **New results.**

Although nearly all of the post-Clotfelter studies surveyed by Steinberg (1990) continue to support the traditional understanding, others question this understanding. Of particular interest are those divisive studies employing observations of the same individuals across time (panel data) to generate elasticity estimates [Broman (1989), Daniel (1989), Frischmann and Lin (1990), and Barrett (1991)].

1.2.4.1 **The panel-data analysis environment.**

Relative to their cross-section and time-series counterparts, elasticity estimates generated from panel data are more likely to be persuasive. Panel data allows researchers to examine how the giving patterns of a particular set of donors changes in response to changes in their individual circumstances. In contrast, cross-sectional data restrict researchers to an examination of how changes in longitudinal circumstances alters longitudinal giving. Similarly, time-series data restrict researchers to an examination of how the giving patterns of "aggregate" individuals\(^{14}\) changes in response to changes in "aggregate"

---

\(^{14}\)An aggregate individual is obtained by summing across the data points of all of the individuals in a given category and then taking the mean. Thus, an aggregate individual is one having the mean contribution, income, price, dependents, marital status, and age for a given income
circumstances. By focusing on how the giving patterns of a particular set of donors changes in response to changes in their individual circumstances, elasticities generated from panel data are more likely to indicate 'true' causality.

In addition, panel-data sets and panel-data estimation techniques offer several important advantages over a conventional cross-sectional or time-series data set. First, panel-data sets provide researchers with a larger number of data points than either a cross-sectional or time-series data set alone is typically capable of providing. Larger samples improve the precision of econometric estimates by increasing the degrees of freedom associated with the estimation. Second, in the case of the panel used in this study, the time dimension of panel data endows price with a source of variation independent of the variation in taxable income, thus reducing the structured collinearity existing between price and disposable income.\textsuperscript{15} Third, panel-data sets make possible the estimation of dynamic behavioral relationships.\textsuperscript{16} By

---

\textsuperscript{15} Specifically, the statutory alteration of tax rates endows price with a source of variation independent of donors' taxable and disposable income. See footnote 38 (page 64) for details.

\textsuperscript{16} The bunching phenomenon is a good case in point. Auten and Rudney (1990) found many donors tend to bunch their gifts in order to derive greater tax benefits. Bunching causes static panel-data estimation models to associate large changes in giving with little or no change in the price
comparison, cross-sectional data sets fail on this count and
time-series data sets usually are unable to provide precise
estimates of the dynamic coefficients. Lastly, panel data's
unique structure improves researchers' ability to control for
heterogeneity across individuals and/or time [e.g., Hsiao
(1986)]. Conventional elasticity estimates are typically
generated from models whose specifications overlook important
explanatory variables (e.g., personal norms of behavior,
educational attainment, and relationships with peer groups)
which proxy for differences in donors' utility functions. The
ideal way of dealing with this heterogeneity is to explicitly
introduce appropriate control variables into the traditional
model. Unfortunately, because observations on these control
variables are seldom available in most data sets, direct
estimation of corresponding parameters is impossible.

Panel-data observations and panel-data estimation
techniques offer a way out of this dilemma. Suppose we are
interested in providing a thorough explanation of donors'
of giving. Consequently, these estimation models tend to bias price
elasticity estimates towards zero. This gives the impression donors are
less sensitive to changes in the price of giving than they really are.

A dynamic model whose specification takes into account donors' habit
persistence and last year's, this year's, and next year's price and income
is one way of dealing with the biasing influence of bunched donations.
By constructing a three year window around this year's giving, the dynamic
models in this study increase the likelihood that donors' response to
bunch-inducing price incentives is reflected in last year's, this year's,
and next year's price elasticities.

Statement of the Problem
giving. Compiling an exhaustive collection of observations on each of the factors influencing giving would prove a formidable task. However, if we were willing to explain changes in these donors' giving, our task is greatly simplified. For example, once donors complete their schooling, the impact of education upon giving probably remains relatively constant over time. A similar argument applies to many other factors such as permanent income, permanent price, permanent habit persistence tendencies, personal norms, and peer groups. Because we have chosen to focus upon explaining changes in giving, only those factors subject to some type of change are useful in explaining changes in charitable giving. Factors having a definite, but constant impact upon giving will not provide much insight into changes in giving. Thus, focusing upon changes, which is only possible with panel-data sets, controls for those factors which exert a definite but constant influence upon donors' giving.

Factors having a definite but constant impact on giving may either be donor specific or time specific. Donor-specific effects may be thought of as the unique but constant influence donor-specific characteristics exert upon charitable giving. The one-way fixed-effects panel-data estimation model controls for donor-specific effects by introducing donor-specific effects.
constants. The one-way random-effects model controls for these effects by treating each donor-specific effect as a realization of a random error term. Time-specific effects are the unique but constant influence each time period exerts upon charitable giving. The two-way fixed-effects panel-data estimation model controls for both individual- and time-specific effects by introducing both donor- and time-specific constants. The two-way random-effects model controls for donor- and time-specific effects by treating them as realizations of random error terms.

1.2.4.2 *Ground-breaking panel-data results.*

As shown in Table 1.2, ground-breaking studies by Broman (1989) and Daniel (1989) report income elasticity estimates that are either of the same order of magnitude as, or considerably smaller than, the representative income elasticity underpinning the traditional understanding. Further, price elasticities are at or near zero. Thus, donors are either more responsive to income-reducing tax payments than they are to price-reducing charitable deductions or just as responsive to both. Consequently, giving is either neutral to, or inhibited by, taxes, ceteris paribus. Further, these price elasticities imply that the deduction is inefficient. Thus, policy makers have ample justification for seeking out
<table>
<thead>
<tr>
<th>TABLE 1.2 INCOME AND PRICE ELASTICITY ESTIMATES FROM BROMAN AND DANIEL'S GROUND-BREAKING STUDIES</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MODEL</strong></td>
</tr>
<tr>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>Representative Elasticity Estimates Underpinning the Traditional Understanding:</td>
</tr>
<tr>
<td>Broman (1989)</td>
</tr>
<tr>
<td>Traditional Model: 1980</td>
</tr>
<tr>
<td>(Standard Errors)</td>
</tr>
<tr>
<td>First-Difference Model: 1981-1982</td>
</tr>
<tr>
<td>(Standard Errors)</td>
</tr>
<tr>
<td>Habit-Persistence Model: 1981-1982</td>
</tr>
<tr>
<td>(Standard Errors)</td>
</tr>
<tr>
<td>First-Difference Future-Price Model: 1980-1981</td>
</tr>
<tr>
<td>(0.07)</td>
</tr>
<tr>
<td>1981-1982</td>
</tr>
<tr>
<td>(Standard Errors)</td>
</tr>
<tr>
<td>Habit-Persistence Future-Price Model: 1980-1981</td>
</tr>
<tr>
<td>(0.12)</td>
</tr>
<tr>
<td>1981-1982</td>
</tr>
<tr>
<td>(0.18)</td>
</tr>
<tr>
<td>Daniel (1989)</td>
</tr>
<tr>
<td>Traditional (Pooled) Model: 1970-1984</td>
</tr>
<tr>
<td>One-Way Static Fixed-Effects Model:</td>
</tr>
<tr>
<td>One-Way Static Random-Effects Model:</td>
</tr>
</tbody>
</table>

**KEY:** $\gamma_{-1}$ = LAST YEAR'S GIVING, $\gamma_0$ = LAST YEAR'S INCOME, $\gamma_{+1}$ = LAST YEAR'S PRICE,

$\gamma_0$ = THIS YEAR'S INCOME, $\gamma_0$ = THIS YEAR'S PRICE, $\gamma_{+1}$ = NEXT YEAR'S INCOME,

$\gamma_{+1}$ = NEXT YEAR'S PRICE, SR = SHORT-RUN, LR = LONG-RUN

Note: The short-run and long-run terminology appearing in this Table should be interpreted in the context of Clotfelter's habit persistence framework (see footnote 12 (page 10) for additional explanation.)

**Statement of the Problem**

20
alternatives to the charitable deduction. In addition, multi-year price-increasing tax reforms will either cause giving to trend upward, or leave giving unaltered, ceteris paribus. This means that nonprofit managers can either count on a steady source of funding or look forward to an increase in financial resources. Thus, at worst, customary levels of goods and services can be maintained.

1.3 Statement Of The Problem.

Because panel-data elasticities are more persuasive, there is now more uncertainty associated with what policy analysts can say about taxation's net effect on giving. This increased uncertainty reduces nonprofit managers' and policy makers' understanding of the charitable-giving phenomenon, thus impeding effective policy decisions and governance of nonprofit organizations. Thus, there is a need for additional empirical work exploring the robustness of panel estimates to alternative model specifications and estimations.

1.4 Research Questions.

By answering the following research questions, this study addresses the interpretational dilemma noted above. Does
statistical analysis verify what logic suggests: that dynamic models of giving dominate static models on statistical, specification, and a priori theoretical grounds? Does the static model provide suitable approximations when data do not allow estimation of the dynamic model? In a full-fledged dynamic model, is the traditional understanding reestablished (taxes encourage giving and charitable contribution deductions are treasury efficient) or additional support found for prior panel estimates? Does the data obey the statistical assumptions necessary for drawing robust inference from these results?

1.5 Research Design.

Figure 1.1 illustrates the research design used in addressing this study's research questions. As argued in earlier sections, the static version of consumer theory is a special case of a more general or dynamic version. Thus, static models of giving should also be special cases of dynamic models. Nearly all previous estimates are generated from static models. Their validity hinges on whether the restrictions necessary for obtaining these estimates are binding.
Statement of the Problem
In order to determine whether dynamic models dominate static models, operational counterparts are identified for each of the theoretical constructs motivated by the dynamic version of consumer theory. When they exist, conventional operationalizations are used. Once identified, a tax calculator is used to generate numerical values for each of these operational counterparts.\textsuperscript{17} The tax calculator draws its raw data from Ernst and Young's 1979-1986 Tax Research Database. Over 200 fields of tax-return information accompanies each appearance of a given taxpayer in the database. Of the 5,786 taxpayers appearing in all eight years of the database, a total of 1,382 satisfy the sample selection criteria used in this study.\textsuperscript{18} Thus, this study's sample has a total of 11,056 observations.

A synthesis of Hsiao's 1986 panel-data monograph and Spanos's (1986) econometric modeling methodology provides an excellent framework for determining whether dynamic models dominate static rivals on statistical and specification

\textsuperscript{17}I would like to thank Joseph Daniel for allowing me to access the program coding that appeared in his original tax calculator. Except for modifications to accommodate tax return information from 1985 and 1986, the tax calculator used in this study is essentially the same one that Daniel used in his 1989 study. Please see Section 3.1.2 (page 72), The tax calculator, for additional discussion.

\textsuperscript{18}See Section 3.1.3 (page 77), The sample, for a discussion of the sample selection criteria used in this study.
grounds. To give due consideration to donor- and time-specific effects in both their fixed and random states, Hsiao's panel-data monograph motivates a total of nine statistical models of giving. Five of these panel-data models are static and four are dynamic.

Each of the estimable models motivated by Hsiao's statistical models of giving is examined for statistical adequacy. A battery of diagnostic tests is used to assess the degree to which each model of giving complies with the assumptions of homoskedasticity, independence, linearity, normality, and parameter stability across time, space, income classes, and tax sophistication. Specification adequacy tests are then used to determine which model provides the best explanation of this year's giving.\(^\text{19}\)

In order to facilitate exposition, Hsiao's statistical models are set forth in Appendix A. Appendix A also contains a formal discussion of the tests used in evaluating each estimable model's statistical adequacy. The results and implications of these tests are found in the concluding portion of this Appendix. Similarly, Appendix B contains a formal discussion of the tests used in determining which model

\(^{19}\text{Specification adequacy addresses whether the improvement in fit of a given model is sufficient to justify its retention. For example, is the improvement in fit achieved by a dynamic model sufficient to justify its retention over a static model?}\)

Statement of the Problem
provides the best explanation of the data. The results and implications of these specification tests are found in the concluding portion of this Appendix.

The model of charitable giving which dominates its rivals on statistical and specification grounds serves as the reference point for evaluating this study's research hypotheses. These research hypotheses follow directly from the refutable propositions summarized in Table 1.1 and facilitate resolution of this study's research questions. The first set of hypotheses is used to determine whether each of the estimated elasticities are statistically significant and have the anticipated signs. Given these individual elasticity estimates are statistically significant, the next two sets of hypotheses use linear combinations of these elasticity estimates to determine whether the charitable deduction achieves short-run and long-run efficiency. Similarly, the last two sets of hypotheses are used to determine whether taxes are neutral in both the short-run and long-run.

---

20 Dominance in an a priori theoretical sense must take place at two levels, logical and empirical. Logical dominance was established in earlier stages of this discussion. Empirical dominance occurs when individual elasticity estimates are significant and have the expected signs.

Statement of the Problem 26
1.6 Findings.

The dynamic two-way fixed-effects model of giving dominates its rivals on statistical, specification, and a priori theoretical grounds. This finding implies that this year's giving is best understood after:

1. Controlling for donor- and time-specific effects.
2. Including conventional measures for this year's income and price elasticities.
3. Taking into account the incremental information contained in last year's giving patterns, income, and price and next year's income and price.

With the exception of next year's marginally significant income elasticity (P = 0.0663), each of the dynamic model's elasticity estimates are highly significant and have the anticipated signs. Because individual elasticity estimates are at least marginally significant, it is appropriate to combine them to accommodate the linear restrictions needed for assessing efficiency and neutrality.

When the scope of analysis is restricted to efficiency, this year's price elasticity estimate of -1.1808 (standard error 0.1158) indicates that the deduction is treasury efficient in the short-run. When efficiency is expanded to include last year's, this year's, and next year's price elasticities, the sum of these elasticities, -0.3985 (0.1691), is greater than negative one. This finding implies that the
deduction is inefficient in the long-run.

When the scope of analysis is expanded to accommodate neutrality, the sum of this year's price and disposable income elasticities is -0.9935 (0.1318). Thus, in the short-run, donors are much more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Consequently, taxes stimulate donors' short-run giving. When neutrality is expanded to include last year's, this year's, and next year's income and price elasticities, the sum of these elasticities is 0.0190 (0.1964). Thus, in the long-run, donors are just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments. In other words, within a three-year window, donors do not change their total contributions, they simply manipulate the timing of these contributions in such a way as to neutralize changes in marginal tax rates.

When taken together, the short-run efficiency and neutrality findings reported above indicate that the deduction is an efficient means of stimulating giving. This finding provides a harmonizing link to the traditional literature. When the dynamic model is restricted to a static portrayal of giving, it yields the same policy and managerial implications as its traditional static counterparts. This means that traditional estimates are probably capturing donors' short-

Statement of the Problem
run response to changes in price and income. In contrast, long-run results suggest that the deduction is an inefficient means of neutralizing donors' response to changes in marginal tax rates. Besides providing a harmonizing link to the traditional literature, these findings provide an interesting contrast to those reported in prior panel studies and underscore the importance of reexamining model specification and estimation.

Although the dynamic two-way fixed-effects model dominates its static and dynamic rivals on statistical, specification, and a priori theoretical grounds, it still suffers from violations of underlying statistical assumptions. This implies that the dynamic model's elasticity estimates may be biased and thus unable to provide reliable insights into theoretical relationships. However, the large sample used in this study may cause pragmatically irrelevant statistical violations to be statistically significant. At worst, the violations of the dynamic two-way fixed-effects model are no more severe than those associated with the econometric models employed in prior research (Please see Appendix A for a full discussion of this issue). For this reason, the results of this study are provided on a "subject-to" basis for interested readers.

Statement of the Problem
1.7 Overview of the Dissertation.

Previous cross-section and time series studies achieved a near-consensus; the deduction is an efficient means of stimulating giving. Recent panel studies, summarized in Chapter 2, found that giving is either neutral to, or inhibited by, taxes, ceteris paribus. Further, the low price elasticities imply that the deduction is inefficient. However, these panel studies were preliminary in nature and failed to exploit consumer theory arguments which transform this year's giving into a dynamic activity. In addition, these studies did not employ many of the econometric techniques and tests which are appropriate for panel data. In Chapter 3, Appendix A, and Appendix B, I introduce a methodology which combines the best aspects of the previous panel studies, a richer utilization of consumer theory, and formal tests of statistical and specification adequacy to produce the estimates reported in Chapter 4. A summary of this study, limitations, and extensions are found in Chapter 5.
2.0 REVIEW OF THE LITERATURE

This chapter reviews the lines of research contributing to the formulation and resolution of this study's research questions. Consequently, this review is restricted to the panel-data studies extended by this study.\textsuperscript{21} Problems with the research designs of prior panel studies raise doubts about their reported conclusions and justify this study.

2.1 Clotfelter.

Clotfelter (1980) begins his study by using observations on itemizing donors from the Treasury's 1967-1973 Panel Study of Income Tax Filers to generate cross-sectional elasticity estimates for the traditional model of giving for the years 1968, 1970, 1972, and 1973.\textsuperscript{22} The reported price elasticities are $-1.67$ (standard error 0.43), $-0.84$ (0.42), $-1.31$ (0.46), and $-1.24$ (0.45), respectively. Corresponding income

\textsuperscript{21}Readers interested in a more exhaustive review of the literature are encouraged to see Clotfelter and Steuerle (1981), Clotfelter (1985), and Steinberg (1990). Subsequent chapters will reference the broader body of literature as necessary to justify variable and model definitions.

\textsuperscript{22}These are the only years in the panel providing observations on charitable giving.

Review of the Literature
elasticities are 0.93 (0.07), 0.96 (0.07), 0.78 (0.09), and
0.90 (0.09). Exploiting the panel-data characteristics of his
data, Clotfelter then provides estimates for the following
partially first-differenced model:23

23 First-difference models are capable of using only two years of the
panel's data for any given estimation. Depending on whether an intercept
term is specified, these first-difference models are special cases of the
more powerful one-way fixed-effects or the two-way fixed-effects model
introduced to this literature by Daniel (1989) or Frischmann and Lin
(1990). To illustrate, consider the following scenario:

A First-Difference Model with an Intercept:
Begin with this expression for explaining levels of giving at time t:

\[ C_{it} = \alpha_0 + \alpha_i + \alpha_t + \beta X_{it} \]  (1)

\( C_{it} \) represents levels of giving at time \( t \). \( \alpha_0 \) is a common intercept term.
\( \alpha_i \) indicates that there is a dummy variable associated with each donor in
order to control for donor-specific effects. Similarly, \( \alpha_t \) indicates that
there is a dummy variable associated with each time period, \( t \). \( \beta \) is a
vector of parameters and \( X_{it} \) is a matrix of observations on this model's
regressors.

Now consider a similar expression for explaining levels of giving at time
\( (t - 1) \):

\[ C_{it-1} = \alpha_0 + \alpha_i + \alpha_{t-1} + \beta X_{it-1} \]  (2)

Subtracting (2) from (1), the following expression for explaining changes
in giving is obtained:

\[ C_{it} - C_{it-1} = (\alpha_0 - \alpha_0) + (\alpha_i - \alpha_i) + (\alpha_t - \alpha_{t-1}) + (\beta X_{it} - \beta X_{it-1}) \]  (3)

Because \( \alpha_0 - \alpha_0 \) and \( \alpha_i - \alpha_i \) are equal to zero, expression (3) becomes:

\[ C_{it} - C_{it-1} = (\alpha_t - \alpha_{t-1}) + (\beta X_{it} - \beta X_{it-1}) \]  (4)

Notice that the term \( \alpha_t - \alpha_{t-1} \) is actually a time-specific intercept
which captures the time trend for the period of change. This result shows
that a first-difference model with an intercept, is actually a special
case of the two-way fixed-effects model because it controls for both
donor- and time-specific effects. In contrast, first-difference models
which lack an intercept term control only for donor-specific effects.

Review of the Literature
\[ \ln G_{12} - \ln G_{11} = \beta_0 + \beta_1 (\ln Y_{i2} - \ln Y_{i1}) + \]
\[ \beta_2 (\ln P_{i2} - \ln P_{i1}) + \beta_3 \text{ MRD} + \]
\[ \beta_4 \text{ AGE (35-54)} + \beta_5 \text{ AGE (55-64)} + \]
\[ \beta_6 \text{ AGE (65+)} + \beta_7 (\text{DEP}_{i2} - \text{DEP}_{i1}) + \epsilon_{it} \]  
(2)

This model is referred to as a partially first-differenced model because nearly all of the demographic variables are not in first-difference form (Broman 1989). First-differencing controls for the unique but constant impact donor-specific characteristics exert upon giving. When an intercept is present, a first-differencing model also controls for time-specific effects (see footnote 23 (page 32) for details). The price elasticity estimates generated by this partially first-differenced model provide a interesting contrast to those generated by traditional cross-sectional models. For the first-difference time periods of 1968-1970, 1970-1972, and 1972-1973, the corresponding price and income elasticities are respectively, \(-0.39 \ (0.27)\) and \(0.45 \ (0.05)\), \(-0.33 \ (0.30)\) and \(0.40 \ (0.06)\), and \(-0.45 \ (0.27)\) and \(0.24 \ (0.05)\). These first-difference estimates are considerably different from those generated by traditional cross-sectional models.

Clotfelter speculates that the disparity between the cross-sectional and partially first-differenced elasticities is due to peculiarities of the data set, the superiority of the partially-differenced model in correcting for donor- and
time-specific heterogeneity, or some other type of specification error. He concludes that the specification of the traditional model is at fault. In particular, he argues that donors' learning about changes in taxes takes place with a delay. Consequently, factors that shaped last giving patterns continue to exert some residual influence on this year's giving. In this case, the static specification of the traditional model of giving fails to capture information about the adjustment process associated with donors' delayed learning response. Thus, estimates from the traditional model are best interpreted as long-run elasticity estimates.

Because the partially first-differenced model focuses on changes, it captures some information about this adjustment process. If the traditional model focuses on the long-run and the partially-differenced model focuses on the short-run, these different orientations should account for the disparity between the estimates of these models. To explore this possibility, Clotfelter introduces the following habit-persistence model:

\[
\begin{bmatrix}
  c_t \\
  c_{t-2}
\end{bmatrix} = \begin{bmatrix}
  c_t^* \\
  c_{t-2}
\end{bmatrix}^\Gamma
\]

(3)

where \( C \) is observed giving, \( C^* \) is the long-run desired level of giving, and \( \Gamma \) represents the coefficient of adjustment.
(0 ≤ τ ≤ 1). If τ is equal to one, donors adjust their giving instantaneously to changes in marginal tax rates.

By taking the natural logs of both sides of equation (3), combining like terms, and using the traditional rather than first-difference model as an operational measure of long-run giving, Clotfelter obtains this habit-persistence model:

\[ \ln G_{it} = \tau [\beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln P_{it} + \mathbf{X} \mathbf{\beta}] + (1 - \tau) \ln G_{t-2} + \epsilon_{it} \]  

(4)

where \( \mathbf{X} \) is a vector of parameters and \( \mathbf{\beta} \) is a vector of demographic variables (age, marital status, and dependents) which proxy for differences in donors utility functions. The habit-persistence model permits empirical assessment of how quickly donors respond to taxation-induced changes in disposable income and price.

For the intervals 1968-1970, 1970-1972, and 1972-1973, the habit persistence model generates short-run price and income elasticities of -0.94 (0.30) and 0.42 (0.06), -0.24 (0.30) and 0.47 (0.07), and -0.49 (0.23) and 0.24 (0.06), respectively. The coefficients of adjustment for these intervals are obtained by taking one minus the coefficient on lagged giving associated with each of these time intervals. The coefficients on lagged giving are respectively, 0.39 (0.05), 0.46 (0.05), and 0.63 (0.05). Thus, the corresponding coefficients of adjustment are 0.61, 0.54, and 0.37,
respectively. These coefficients of adjustment imply that the long-run price and income elasticities for each of these intervals are $-1.55$ (0.51) and $0.70$ (0.12), $-0.45$ (0.56) and $0.87$ (0.15), and $-1.34$ (0.65) and $0.67$ (0.17), respectively.\textsuperscript{24}

When interpreted in the context of his sample, Clotfelter's coefficients of adjustment imply donors' habitual consumption of giving greatly impedes the responsiveness of their giving to taxation-induced changes in disposable income and price. For example, the coefficients for the 1968-1970 and 1970-1972 time intervals imply that only 61 and 54 percent of the total change in long-run giving takes place within two years. While the coefficient for the 1972-1973 interval implies that only 37 percent of the total change in long-run giving takes place within one year. Further, these coefficients imply that six years pass before roughly 90 percent of the change is realized.\textsuperscript{25}

Clotfelter concludes that short-run elasticity estimates from the habit-persistence model are roughly of the same order

\textsuperscript{24}Long-run coefficients are obtained by taking the short-run coefficients and dividing them by their respective coefficients of adjustment. Thus, in the case of the 1968-1970 interval, the long-run income and price elasticities are obtained as follows: $(0.42 / 0.61) = 0.70$ and $(-0.94 / 0.61) = -1.55$

\textsuperscript{25}The 90 percent adjustment measures are obtained as follows: $\left(1 - (0.39)^2\right)$, $\left(1 - (0.46)^3\right)$, and $\left(1 - (0.63)^6\right)$. The third power indicates three two-year periods or six years have lapsed and the sixth power indicates that six one-year periods have lapsed.
of magnitude as those generated from his partially first-differenced model. In addition, the long-run elasticities implied by the habit-persistence model are also roughly consistent with traditional estimates. Thus, traditional estimates are apparently reliable indicators of donors' long-run response to changes in marginal tax rates. The estimates from the partially first-differenced model are merely picking up donors' short-run response to taxation-induced changes in disposable income and price. These results seem to provide continued support for concluding that the deduction is an efficient means of stimulating donors' giving. That is, the price elasticity is less than or equal to negative one and donors are more responsive to price-reducing charitable deductions than they are to income-reducing tax payments.

2.2 Broman.

Like Clotfelter, Broman (1989) begins by establishing a comparative link to traditional income and price elasticity estimates. Using observations on itemizing donors from the 1979-1982 Ernst and Young Tax Research Database, Broman reports that the 1982 income and price elasticities (0.82 (0.11) and -1.03 (0.38)) generated by a cross-sectional version of the traditional model are consistent with
traditional estimates. Broman then introduces model specifications that extend and correct for inconsistencies she believes exist in the models used by Clotfelter. Broman's initial first-difference model is specified as follows:

\[
\ln G_{i2} - \ln G_{i1} = \beta_0 + \beta_1 (\ln Y_{i2} - \ln Y_{i1}) + \\
\beta_2 (\ln P_{i2} - \ln P_{i1}) + \\
\epsilon (Z_{i2} - Z_{i1}) + \epsilon_{it}
\]

(5)

where the subscript \(i\) refers to the \(i\)th donor and the numerical subscripts indicate time periods. Broman's first-differencing of the vector of demographic variables stands in contrast to Clotfelter's partially-differenced vector of demographic variables. Broman believes first-differencing each of the variables appearing in a first-difference model facilitates comparisons between the traditional model, equation (1), and the first-difference model, equation (5). Because equation (5) is exactly equation (1) in first-difference form, differences in the results of the two models are apparently attributable solely to differences in the error terms. For the roughly comparable first-difference interval of 1981-1982, the income and price elasticities from the first-difference model, 0.24 (0.07) and -0.22 (0.23), provide a striking contrast to those of the traditional cross-sectional model.

To examine whether the disparity between traditional and

Review of the Literature
first-difference estimates is attributable to donors' habit persistence, Broman modifies her first-difference model and obtains the following habit-persistence model:

\[
\ln G_{12} - \ln G_{11} = \Gamma [\beta_0 + \beta_1 (\ln Y_{i2} - \ln Y_{i1}) + \beta_2 (\ln P_{i2} - \ln P_{i1}) + \mu (Z_{i2} - Z_{i1})] + (1 - \Gamma) [\ln G_{i1} - \ln G_{i0}] + w_{it}
\]  

(6)

Broman's habit-persistence model differs in an important way from Clotfelter's. Recall Clotfelter uses the traditional model appearing in equation (1) rather than a first-difference model to operationalize long-run giving. As noted earlier, the traditional model fails to control for heterogeneity across donors and time. This oversight may bias the estimate of \( \Gamma \) in favor of the hypothesis that giving adjusts with a lag.

Acceptance of the lag hypothesis implies that the difference between the estimates of the traditional model and those of the first-differenced model is attributable to the short-run orientation of the first-difference model rather than the influence of heterogeneity across donors and time. For the time interval 1981-1982, Broman's habit persistence model generates short-run income and price elasticities of 0.26 (0.07) and -0.28 (0.24), respectively. Because the coefficient associated with last year's gifts is 0.32 (0.18),
the coefficient of adjustment is 0.68. This implies that the corresponding long-run income and price elasticities are 0.38 and -0.41 (no standard errors reported), respectively. Surprisingly, these long-run elasticities are similar to the short-run elasticities.

These results suggest that donors respond quite rapidly to taxation-induced changes in disposable income and price. In Broman's estimation setting, the coefficient of adjustment implies that 90 percent of donors' response to changes in marginal tax rates takes place within two years. Therefore, the habit-persistence argument does not provide a reasonable explanation of why the elasticity estimates from the first-difference models are at odds with traditional estimates.

To pursue this disparity issue further, Broman expands her first-difference, equation (5), and habit-persistence, equation (6), models by adding an expectation variable to account for the changes in this year's giving brought about by anticipated changes in next year's price of giving. This is the resulting first-difference future-price model:

\[ \ln G_{t2} - \ln G_{t1} = \beta_0 + \beta_1 (\ln Y_{t2} - \ln Y_{t1}) + \beta_2 (\ln P_{t2} - \ln P_{t1}) + H (Z_{t2} - Z_{t1}) + \beta_3 (\ln E_{t2}(P) - \ln E_{t1}(P)) + w_{it} \]  

(7)

where \( E_{t2}(P) \) represents donors' expectation at time = 2 of some future price and \( E_{t1}(P) \) represents donors' time-equal-
one expectation of price at time $t = 2$. This is the resulting habit-persistence future-price model:

$$\ln G_{12} - \ln G_{11} = \gamma \left[ \beta_0 + \beta_1 (\ln Y_{12} - \ln Y_{11}) + \beta_2 (\ln P_{12} - \ln P_{11}) + \mu (Z_{12} - Z_{11}) \right] + (1 - \gamma) \left[ \ln G_{11} - \ln G_{10} \right] + \beta_3 (\ln E_{12}(\frac{P}{P_1}) - \ln E_{11}(\frac{P}{P_2})) + \epsilon_{it}$$  \hspace{1cm} (8)

Accounting for donors' expectation formation is an innovative contribution to the literature and represents the first step towards a fully dynamic model of charitable giving.

The income and price elasticities generated by the first-difference future-price model for time intervals 1980-1981 and 1981-1982 are respectively, 0.14 (0.08) and -0.48 (0.28) and 0.24 (0.08) and -0.21 (0.23). Comparable income and price elasticities from the habit-persistence future-price model are 0.15 (0.07) and -0.48 (0.28) and 0.26 (0.07) and -0.27 (0.24), respectively. These elasticities are quite similar to those generated from Broman's first-difference and habit-persistence models.

For the time intervals 1980-1981 and 1981-1982, the habit-persistence future-price model has coefficients associated with last year's giving of 0.10 (0.12) and 0.31 (0.18), respectively. Corresponding coefficients of adjustment are 0.90 and 0.69. Thus, long-run income and price elasticities for these two time intervals are respectively,
0.17 and -0.53 and 0.38 and -0.39 (no standard errors reported). In addition, the coefficients associated with next year's price are 1.03 (0.51) and 0.25 (0.93), respectively. Please notice that there is only period-specific (statistical significance in one time interval and not in the other) evidence that last year's giving patterns exert some residual influence on this year's giving. A similar conclusion holds for next year's price.

In summary, Broman's empirical evidence suggests that the price elasticity is at or near zero and donors are either slightly more responsive to income-reducing tax payments than they are to price-reducing charitable deductions or just as responsive to both. Thus, the deduction is treasury inefficient and charitable giving is either inhibited by, or neutral to taxes. Contrary to Clotfelter's claim, donors' indifference to price-reducing charitable deductions is not attributable to their delayed learning about changes in taxes. Instead, the ability of Broman's first-difference models to control for donor- and time-specific heterogeneity seems to account for the difference between estimates generated by the traditional and first-difference models.\(^26\)

\(^{26}\)Because Broman specifies an intercept term in each of the first-difference models, she has essentially taken into account the time-specific effects found in each two-year first-differencing interval. See footnote 23 (page 32) for a more detailed discussion of this point.
2.3 Daniel.

Daniel (1989) concludes that neither Clotfelter (1980) nor Broman (1989) utilize econometric estimation techniques which fully exploit the information content of their panels. Their first-difference models are capable of utilizing only two years of the data in any given estimation. Daniel shows that these models are special cases of more general fixed-effects estimators. These fixed-effects estimators are able to draw upon all of the data in a panel when generating parameter estimates. This exhaustive utilization of the panel's information permits researchers to draw upon a larger number of observations, thus leading to more precise parameter estimates than those generated in the limited two-period setting of first-difference estimation.

After indicating that the income and price elasticities generated by a pooled or cross-sectional model of giving for the time interval 1979-1984 are respectively, 0.66 (0.04) and -1.31 (0.15), Daniel transforms Broman's first-difference model of giving, equation (5), to accommodate one-way panel-data estimation techniques. Using observations on itemizing donors from the 1979-1984 Ernst and Young Tax Research Database, parameters are obtained for the one-way fixed-effects model by performing an Ordinary Least Squares regression on this equation:

Review of the Literature
\[ \ln G_{it} - \ln G_i = \beta_1 \ln P_{it} - \ln P_i + \beta_2 \ln Y_{it} - \ln Y_i + H [\bar{Z}_{it} - \bar{Z}_i] + W_{it} ; \quad i = 1, \ldots, N; \quad t = 1, \ldots, T \]  

where \( \ln G_i, \ln P_i, \ln Y_i, \) and \( Z_i \) represent the respective variable's average over time for a particular donor. Thus, for a given donor, each period's observation on a particular variable enters into the regression as a deviation from its average over time. The one-way fixed-effects panel-data estimator generates income and price elasticities of 0.48 (0.03) and -0.03 (0.04), respectively.

Daniel notes that first-difference and one-way fixed-effects estimators are appropriate when donor and time-specific effects manifest themselves as constants. If these effects are more appropriately thought of as realizations of random variables, then in the case of donor-specific effects, this one-way random-effects estimator applies:

\[ \ln G_{it} - [(1 - (R)^{1/2}) \ln G_i] = \beta_1 \ln P_{it} - (1 - (R)^{1/2}) \ln P_i + \beta_2 \ln Y_{it} - (1 - (R)^{1/2}) \ln Y_i + H [Z_{it} - (1 - (R)^{1/2}) Z_i] + W_{it} \]  

where \( R \) depicts proportionately \( 0 \leq R \leq 1 \) the extent to which donors are homogenous. As \( R \) approaches one, the heterogeneity weighting factor, \( (1 - (R)^{1/2}) \), approaches zero,

Review of the Literature
indicating that no weight is given to donor heterogeneity. Consequently, this general least squares estimator (one-way random-effects) approaches an ordinary least squares estimation on pooled data. On the other hand, as $R$ approaches zero, the heterogeneity weighting factor approaches one, indicating that full weight is given to donor heterogeneity in computing parameter estimates. In this case, the general least squares estimator (one-way random-effects estimator) approaches the one-way fixed-effect estimator. Thus, the general least squares estimator provides an intermediate solution between the extremes of treating all donors as heterogeneous (i.e., the fixed-effects case) or treating all donors as homogeneous (i.e., the pooling case where all of the observations on each donor are combined into a single, large cross-section). If the estimates generated by the two different estimators differ substantially, the fixed-effects estimators are preferred because they are more robust than the random-effects estimator.\textsuperscript{27} The income and price elasticities generated by the one-way random-effects model (i.e., the general least squares model) are 0.52 (0.03) and -0.19 (0.07),

\textsuperscript{27}As noted by Daniel, these fixed-effects estimators are unbiased and consistent regardless of whether the donor-specific effects are random or fixed. In addition, these estimators are more robust to misspecification, particularly in the likely case where donor-specific effects are correlated with the included independent variables.

Review of the Literature 45
respectively.

Like those generated by Broman, the elasticity estimates generated by Daniel's one-way fixed- and random-effects models call into question traditional estimates. The fixed-effects and random-effects analyses provide empirical support for concluding that the price elasticity is greater than negative one and donors are much more responsive to income-reducing tax payments than they are to price-reducing deductions. Thus, taxes inhibit giving and the deduction is inefficient.

2.4 Frischmann and Lin.

Using observations on itemizing donors from Ernst and Young's 1979-1986 Tax Research Database, Frischmann and Lin (1990) begin their study by generating new elasticity estimates from the traditional or pooled model and the one-way fixed- and random-effects models. The resulting traditional or pooled income and price elasticities are 0.72 (0.04) and -0.95 (0.14), respectively. Corresponding income and price elasticities for the one-way fixed- and random-effects models are 0.55 (0.03) and 0.18 (0.10) and 0.59 (0.03) and 0.00 (0.10), respectively. These estimates are roughly in harmony with, and provide a comparative link to, Broman and Daniel's work.
Frischmann and Lin then extend Daniel's one-way estimation framework by transforming equations (9) and (10) into two-way fixed- and random-effect panel-data estimators. These two-way estimation models control for both donor- and time-specific effects (the unique but constant influence each time period exerts upon donors' giving). The two-way fixed-effects model generates income and price elasticities estimates of 0.39 (0.04) and -0.39 (0.12), respectively. The two-way random-effects model has corresponding elasticities of 0.44 and -0.55 (no standard errors reported).

The elasticity estimates generated by Frischmann and Lin's one-way fixed- and random-effects models continue to tell the now familiar story. The price elasticity is greater than negative one and donors are much more responsive to income-reducing tax payments than they are to price-reducing charitable deductions. This implies that the deduction is inefficient and giving is inhibited by taxes. Although still indicating that the price elasticity is greater than negative one, the two-way fixed- and random-effects models suggest that donors are just as responsive to income-reducing tax payments as they are to price-reducing charitable deductions. In this case, the deduction is an inefficient means of ensuring that giving is neutral to taxes. Both the one-way and two-way panel-data elasticity estimates offer an interesting contrast.
to traditional cross-section and time-series estimates.

2.5 Barrett.

Reflecting a synthesis of prior panel-data techniques, Barrett (1991) examines the specification adequacy of several static and dynamic (as narrowly defined by Broman) models of giving. The final comparison contrasts the 'best' static and dynamic models of giving. Relative to its static counterpart, the dynamic two-way fixed-effects model offers statistically preferred insight into donors' giving. This empirical evidence implies that donor-specific effects, time-specific effects, last year's giving, and next year's price are very important considerations in properly assessing the deduction's efficiency and whether giving is neutral to changes in marginal tax rates.

Using the dynamic two-way fixed-effects model as the point of reference, several findings are of interest. The

\[28\] As an aside to the interested reader, the pooled or cross-sectional model of giving generated income and price elasticity estimates of 0.87 (0.04) and -0.59 (0.11), respectively. Corresponding estimates for the static one-way fixed-effects, one-way random-effects, and two-way fixed-effects models are 0.62 (0.03) and 0.18 (0.08), 0.69 (0.03) and 0.05 (0.07), and 0.34 (0.04) and -0.82 (0.10), respectively. The dynamic one-way fixed- and random-effects models generate income and price elasticities of 0.42 (0.03) and -0.52 (0.10) and 0.19 (0.03) and -0.72 (0.09), respectively.

Review of the Literature
elastici ty estimate associated with last year giving, 0.16 (0.01), suggests that donors' learning about changes in taxes takes place with a very small delay. Thus, last year's giving patterns exert only minor influence on this year's giving. In particular, a 10 percent increase in last year's giving results in roughly a 2 percent increase in current giving, ceteris paribus. Conversely, a 10 percent decrease in last year's giving reduces this year's giving by roughly 2 percent, ceteris paribus. Interpreted in Clotfelter's habit-persistence framework, the complement of this elasticity yields a coefficient of adjustment of 0.84. Consequently, 84 percent of the long-run taxation-induced change in giving is realized within one year. Ninety-eight percent of the change is realized within two years. Because donors respond so rapidly to taxation-induced changes in disposable income and price, Clotfelter's distinction between donors' short- and long-run response to changes in taxation is trivial and, thus, abandoned.

The elasticity estimate associated with this year's disposable income, 0.23 (0.04), is also highly significant and has the usual sign. Although in harmony with Broman's, the magnitude of this estimate is considerable smaller than traditional estimates. The disparity between estimates is reconciled if this year's income is interpreted as donors'
response to changes in transitory income. The elasticity estimate associated with this year's price, \(-1.09 (0.11)\), is highly significant and has the anticipated sign. This evidence suggests that donors respond to transitory increases in this year's price by shifting a portion of their intended giving into subsequent years. In particular, a 10 percent increase in this year's price brings about an 11 percent reduction in this year's giving, ceteris paribus. Conversely, donors respond to decreases in this year's price by giving more this year.

The elasticity associated with next year's highly significant positively-signed price elasticity of 0.31 (0.10) is also in harmony with empirical evidence reported by Broman. This evidence implies that donors who face rising prices next year shift a portion of their anticipated giving into 'this' year. Thus, a 10 percent increase in next year's price increases this year's giving by 3 percent. Conversely, this year's giving decreases when donors face lower prices next year.

Because individual elasticity estimates are highly

---

29. Recall that panel-data estimation techniques control for factors having a definite but constant impact upon giving. Because permanent income and price are by definition constant, the influence they exert on this year's giving is included in donor-specific effects. Consequently, price and income elasticities must be capturing donors' response to transitory changes in income and price.
significant, combining them to form the linear restrictions needed for assessing giving's efficiency and neutrality is a meaningful way to proceed. When the analysis is restricted to this year's price elasticity, the charitable deduction is efficient. That is, this year's price elasticity is less than or equal to negative one. When the analysis is expanded to include both this year's and next year's price elasticities, the efficiency of charitable deductions cannot be rejected.\textsuperscript{30} However, the point estimate or sum of these elasticity estimates, (-0.78), suggests that the deduction is probably inefficient in the long-run.

Having examined efficiency, the scope of analysis is expanded to include this year's disposable income elasticity. When neutrality is restricted to this year's disposable income and price elasticities, the sum of these elasticities, -0.8532, is statistically different from zero and suggests that donors are much more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Thus, taxes stimulate giving.

If neutrality is expanded to include next year's price elasticity, the sum of this year's income and price

\textsuperscript{30}In order to provide additional comfort, the reader should note that the sum of this year's and next year's price elasticities is also statistically different from zero.

\textbf{Review of the Literature} 51
elasticities and next year's price elasticity, -0.55, is still statistically different from zero. Thus, even with a broader definition of neutrality, donors are more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Consequently, increases in marginal tax rates continue to stimulate giving.

The short-run findings reported above provide a harmonizing link to traditional estimates. When the dynamic model's interpretational insights are restricted to assessing how changes in this year's disposable income and price influence this year's giving, donors respond to income-reducing tax payments and price-reducing charitable deductions in precisely the same way as do donors in traditional samples. In addition, the deduction is efficient. Thus, traditional estimates seem to reflect donors' short-run response to changes in this year's income and price. This finding dispels some of the uncertainty associated with the literature's empirical insight into whether the deduction is treasury efficient and taxes are neutral in the short-run.

2.6 Summarizing the Panel-Data Literature.

The elasticity summaries contained in Tables 2.2 and 2.3 and the preceding discussions concerning first-difference and one-way panel-data models, indicate that donors are:

Review of the Literature
### Table 2.1 A Summary of the Elasticity Estimates Reported by Clotfelter and Broman

<table>
<thead>
<tr>
<th></th>
<th>( c_{-1} )</th>
<th>( y_0 )</th>
<th>( p_0 )</th>
<th>( p_{+1} )</th>
<th>Efficiency</th>
<th>Neutrality</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Clotfelter (1980)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Static Models:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traditional Model:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1968-1970</td>
<td>0.06</td>
<td>-0.84</td>
<td>(0.07)</td>
<td>(0.42)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970-1972</td>
<td>0.76</td>
<td>-1.31</td>
<td>(0.09)</td>
<td>(0.46)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1972-1973</td>
<td>0.90</td>
<td>-1.24</td>
<td>(0.09)</td>
<td>(0.45)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>First-Difference Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1968-1970</td>
<td>0.45</td>
<td>-0.39</td>
<td>(0.05)</td>
<td>(0.27)</td>
<td>INEFFICIENT</td>
<td>NEUTRAL</td>
</tr>
<tr>
<td>1970-1972</td>
<td>0.40</td>
<td>-0.33</td>
<td>(0.06)</td>
<td>(0.30)</td>
<td>INEFFICIENT</td>
<td>NEUTRAL</td>
</tr>
<tr>
<td>1972-1973</td>
<td>0.24</td>
<td>-0.45</td>
<td>(0.05)</td>
<td>(0.27)</td>
<td>INEFFICIENT</td>
<td>STIMULATES</td>
</tr>
<tr>
<td>Habit-Persistence Model</td>
<td>0.39</td>
<td>0.42</td>
<td>0.70</td>
<td>-0.94</td>
<td>INEFF. EFF.</td>
<td>STIM. STIM.</td>
</tr>
<tr>
<td>1968-1970</td>
<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.12)</td>
<td>(0.30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1970-1972</td>
<td>0.46</td>
<td>0.47</td>
<td>0.87</td>
<td>-0.24</td>
<td>INEFF. INEFF.</td>
<td>INHIB. INHIB.</td>
</tr>
<tr>
<td>1972-1973</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td>(0.15)</td>
<td>(0.30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.24</td>
<td>0.67</td>
<td>-0.49</td>
<td>INEFF. EFF.</td>
<td>STIM. STIM.</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.06)</td>
<td>(0.17)</td>
<td>(0.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Broman (1980)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Static Models:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traditional Model:</td>
<td>0.82</td>
<td>-1.03</td>
<td>(0.11)</td>
<td>(0.38)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>First-Difference Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1961-1962</td>
<td>0.24</td>
<td>-0.22</td>
<td>(0.07)</td>
<td>(0.23)</td>
<td>INEFFICIENT</td>
<td>NEUTRAL</td>
</tr>
<tr>
<td>Habit-Persistence Model</td>
<td>0.32</td>
<td>0.26</td>
<td>0.38</td>
<td>-0.28</td>
<td>INEFF. INEFF.</td>
<td>NEUT. NEUT.</td>
</tr>
<tr>
<td>1981-1982</td>
<td>(0.18)</td>
<td>(0.07)</td>
<td>--</td>
<td>(0.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dynamic Models:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First-Difference</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Future-Price Model:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980-1981</td>
<td>0.14</td>
<td>-0.48</td>
<td>(0.08)</td>
<td>(0.28)</td>
<td>INEFFICIENT</td>
<td>STIMULATES</td>
</tr>
<tr>
<td>1981-1982</td>
<td>0.24</td>
<td>-0.21</td>
<td>(0.07)</td>
<td>(0.23)</td>
<td>INEFFICIENT</td>
<td>NEUTRAL</td>
</tr>
<tr>
<td>Habit-Persistence</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Future-Price Model:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1980-1981</td>
<td>0.10</td>
<td>0.15</td>
<td>0.17</td>
<td>-0.48</td>
<td>INEFF. INEFF.</td>
<td>STIM. STIM.</td>
</tr>
<tr>
<td>1981-1982</td>
<td>0.31</td>
<td>0.26</td>
<td>0.38</td>
<td>-0.27</td>
<td>INEFF. INEFF.</td>
<td>NEUT. NEUT.</td>
</tr>
</tbody>
</table>

**Key:** \( c_{-1} \) = Last year's contribution, \( y_{-1} \) = Last year's disposable income,

\( p_{-1} \) = Last year's price, \( y_{0} \) = This year's disposable income,

\( p_{0} \) = This year's price, \( y_{+1} \) = Next year's disposable income,

\( p_{+1} \) = Next year's price, \( sr \) = Short-run, \( lr \) = Long-run

Note: The terms short- and long-run should be interpreted within the habit-persistence framework.

Review of the Literature 53
1. More responsive to income-reducing tax payments than they are to price-reducing charitable deductions (see Clotfelter's 1970-1972 habit-persistence model, Daniel's one-way models, Frischmann and Lin's one-way models, and Barrett's one-way static models).


Thus, giving is stimulated by, inhibited by, or neutral to taxes. Further, with the exception of Clotfelter's 1968-1970 and 1972-1973 habit-persistence models, first-difference and one-way panel-data estimates of the price elasticity are all greater than negative one. This means that the charitable deduction is probably treasury inefficient. These findings suggest nonprofit managers can anticipate increases, decreases, or no change in giving during price-increasing tax reforms. An increase, decrease, or no change in giving means that nonprofit managers can, at worst, anticipate having to restrict their customary levels of goods and services unless alternative funding is obtained. In addition, from an
<table>
<thead>
<tr>
<th></th>
<th>a_{t-1}</th>
<th>a_{t0}</th>
<th>a_{t1}</th>
<th>EFFICIENCY</th>
<th>NEUTRALITY</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Daniel (1999)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-Sectional or</td>
<td>0.66</td>
<td>-1.31</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pooled Model 1979-1984:</td>
<td>(0.04)</td>
<td>(0.15)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Static</td>
<td>0.48</td>
<td>-0.03</td>
<td></td>
<td>INEFFICIENT</td>
<td>INHIBITS</td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.03)</td>
<td>(0.04)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Static</td>
<td>0.52</td>
<td>-0.19</td>
<td></td>
<td>INEFFICIENT</td>
<td>INHIBITS</td>
</tr>
<tr>
<td>Random-Effects Model:</td>
<td>(0.03)</td>
<td>(0.07)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Frischmann and Lin (1990)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-Sectional Model:</td>
<td>0.72</td>
<td>-0.95</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1979-1986</td>
<td>(0.04)</td>
<td>(0.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Static</td>
<td>0.55</td>
<td>0.18</td>
<td></td>
<td>INEFFICIENT</td>
<td>INHIBITS</td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.03)</td>
<td>(0.10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Static</td>
<td>0.59</td>
<td>0.00</td>
<td></td>
<td>INEFFICIENT</td>
<td>INHIBITS</td>
</tr>
<tr>
<td>Random-Effects Model:</td>
<td>(0.03)</td>
<td>(0.10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-Way Static</td>
<td>0.39</td>
<td>-0.39</td>
<td></td>
<td>INEFFICIENT</td>
<td>NEUTRAL</td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.04)</td>
<td>(0.12)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-Way Static</td>
<td>0.44</td>
<td>-0.55</td>
<td></td>
<td>INEFFICIENT</td>
<td>NEUTRAL</td>
</tr>
<tr>
<td>Random-Effects Model:</td>
<td>--</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Barrett (1991)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-Sectional Model:</td>
<td>0.87</td>
<td>-0.59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1979-1986</td>
<td>(0.04)</td>
<td>(0.11)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Static</td>
<td>0.62</td>
<td>0.18</td>
<td></td>
<td>INEFFICIENT</td>
<td>INHIBITS</td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.03)</td>
<td>(0.08)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Static</td>
<td>0.69</td>
<td>0.05</td>
<td></td>
<td>INEFFICIENT</td>
<td>INHIBITS</td>
</tr>
<tr>
<td>Random-Effects Model:</td>
<td>(0.03)</td>
<td>(0.07)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Two-Way Static</td>
<td>0.34</td>
<td>-0.82</td>
<td></td>
<td>STIMULATES</td>
<td></td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.04)</td>
<td>(0.10)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-Way Dynamic</td>
<td>0.17</td>
<td>0.42</td>
<td>-0.52</td>
<td>0.57</td>
<td></td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.10)</td>
<td>(0.09)</td>
<td></td>
</tr>
<tr>
<td>One-Way Dynamic</td>
<td>0.76</td>
<td>0.19</td>
<td>-0.72</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>Random-Effects Model:</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.09)</td>
<td>(0.08)</td>
<td></td>
</tr>
<tr>
<td>Two-Way Dynamic</td>
<td>0.16</td>
<td>0.23</td>
<td>-1.09</td>
<td>0.31</td>
<td></td>
</tr>
<tr>
<td>Fixed-Effects Model:</td>
<td>(0.01)</td>
<td>(0.04)</td>
<td>(0.11)</td>
<td>(0.10)</td>
<td></td>
</tr>
</tbody>
</table>

**KEY:** $c_{t-1} =$ LAST YEAR'S CONTRIBUTION, $y_{t-1} =$ LAST YEAR'S DISPOSABLE INCOME,

$P_{t-1} =$ LAST YEAR'S PRICE, $y_{t0} =$ THIS YEAR'S DISPOSABLE INCOME,

$P_{t1} =$ THIS YEAR'S PRICE, $y_{t1} =$ NEXT YEAR'S DISPOSABLE INCOME,

$P_{t+1} =$ NEXT YEAR'S PRICE, SR = SHORT-RUN, LR = LONG-RUN

Note: The terms short- and long-run should not be interpreted in the habit-persistence framework. Rather, they should be thought of as relative indicators. That is, the summation of this and next year's price elasticities cover a longer time frame than this year's price elasticity alone.

$SR = -0.52, LR = -0.52 + 0.57.

$LR = -0.52 + 0.42, LR = -0.52 + 0.57 + 0.42$

Review of the Literature 55
efficiency perspective, it appears that policy makers have a case for seeking out alternatives to the charitable deduction. These alternatives should simultaneously provide an efficient subsidy and neutralize donors response to changes in marginal tax rates.

Depending on the scope of taxation and whether giving is portrayed as a static or dynamic activity, two-way panel-data models suggest that donors are:

1. More responsive to price-reducing charitable deductions than they are to income-reducing tax payments (see Barrett's two-way models).

2. Just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments (see Frischmann and Lin's two-way models).

Thus, giving is either inhibited by, or neutral to taxes. Further, price elasticities are either less than or equal to negative one (see Barrett's two-way dynamic fixed-effects model as applied to the short-run) or greater than negative one (see Frischmann and Lin's two-way models and Barrett's two-way static fixed-effects model and two-way dynamic fixed-effects model as applied to the long-run). Thus, the deduction is either treasury efficient or inefficient. These two-way panel-data findings imply that nonprofit managers can count on having to find alternative resources or a steady source of funding. In addition, because the deduction is either an efficient or inefficient means of stimulating

Review of the Literature 56
giving, policy makers have a case for either retaining the charitable deduction or seeking out alternatives which provide an efficient subsidy.

Because panel-data elasticities are more persuasive, the sensitivity of these elasticity estimates to minor variations in model specification is quite disconcerting. Besides undermining the traditional understanding, panel estimates are unable to offer a consensus of their own. The resulting uncertainty reduces nonprofit managers' and policy makers' understanding of the charitable-giving phenomena, thus impeding effective policy decisions and governance of nonprofit organizations.

2.7 Extending the Panel-Data Literature.

The uncertainty caused by panel estimates is largely attributable to the piecemeal way in which a body of new knowledge is accumulated. During the transition towards a consensus, each model is given equal standing until one model is shown to dominate its rivals on statistical, specification, and a priori theoretical grounds. By using a methodology which combines the best aspects of the previous panel studies, a richer utilization of consumer theory, and formal tests of statistical and specification adequacy, a dynamic model of

Review of the Literature
giving is found that dominates its rivals on each of these grounds. The policy implications of this dominant model should be given precedence over those of its rivals.

The methodological details used in establishing the dynamic model's statistical and specification dominance are found in Appendix A and Appendix B. The dynamic model's a priori dominance is shown logically in Chapter 1 and then demonstrated empirically in Chapters 3 and 4 and Appendices A and B. The policy implications suggested by this empirical evidence are summarized in Chapter 5.
3.0 RESEARCH DESIGN

In harmony with the research design sketched in Figure 1.1, this Chapter, along with Appendix A and B, makes the transition from the theoretical to the empirical realm. The introductory sections define operational counterparts for the theoretical constructs introduced in Chapter 1, discuss the tax calculator that generates numerical values for each of these operational counterparts, and reveal sample selection criteria and descriptive statistics for the resulting sample.

The discussion then turns to the econometric framework underpinning this study. Briefly, a synthesis of Hsiao's 1986 panel-data monograph and Spanos's (1986) econometric modeling methodology provides an excellent framework for determining whether dynamic models dominate static rivals on statistical, specification, and a priori theoretical grounds. Giving due consideration to donor- and time-specific effects in both their fixed and random states, Hsiao's panel-data monograph motivates a total of nine statistical models of giving. Five of these models are static and four are dynamic.

Each of the estimable models motivated by Hsiao's statistical models is examined for statistical adequacy. A battery of diagnostic tests is used to assess the degree to
which each static and dynamic model complies with the underlying assumptions of homoskedasticity, independence, linearity, normality, and parameter stability across time, space, income classes, and tax sophistication. Specification adequacy tests are then used to determine which model provides the best explanation of this year's charitable contributions.

To facilitate exposition, Hsiao's statistical models are set forth in Appendix A. Appendix A also contains a formal discussion of the tests used in evaluating each estimable model's statistical adequacy. The results and implications of these tests are found in the concluding portion of this Appendix. Similarly, Appendix B contains a formal discussion of the tests used in determining which model provides the best explanation of the data. The results and implications of these specification tests are found in the concluding portion of this Appendix.

Foreshadowing, the dynamic two-way fixed-effects model dominates its dynamic and static rivals on statistical, specification, and a priori theoretical grounds. This dynamic model is used as an organizing framework for examining this study's research hypotheses. These hypotheses and their accompanying test statistics are found in the latter portions of this Chapter.
3.1 Some Operational Preliminaries.

Each estimable model appearing in this study draws upon a common body of knowledge. The theoretical portion of this knowledge appears primarily in Chapter 1. The operational portion appears here to disencumber subsequent discussion.

3.1.1 Defining operational variables.

Testing consumer theory's refutable propositions requires operational counterparts for charitable giving's theoretical constructs. Several interesting issues arise when defining and generating these operational counterparts. These issues and their resolutions are now examined.

3.1.1.1 Conventional surrogates.

Charitable contributions. Annual contributions are operationalized as the sum of cash and noncash gifts.\textsuperscript{31} Non-

\textsuperscript{31}This operationalization does not reflect nondeductible gifts of time and private acts of charity (see Schiff 1985, 1990 for insight into how taxes influence gifts of time). Thus, donors' price of giving and transfers of resources from personal to public consumption may be understated. To clarify, if nondeductible gifts of time and private acts of charity were included, donors' taxable income would be reduced. The reductions in taxable income would probably reduce donors' marginal tax rates, thus increasing price. Said differently, gifts that are not deducted have a price of one dollar. In the absence of individual-specific data on alternative forms of charity and because taxation induces deductible gifts, this operationalization provides a conventional and reasonable surrogate for 'true' giving.
contributing itemizers are assumed to have made gifts of $10.\textsuperscript{32} Each contribution total is examined for compliance with mandated ceilings.\textsuperscript{33,34} Allowable deductions are then restated in terms of 1982 dollars.\textsuperscript{35} Each restated deduction

\textsuperscript{32}This assumption allows noncontributing itemizers to be included in estimations of the log-linear model [e.g., Clotfelter and Steurle (1981)]. Noncontributing itemizers account for less than 4% of the total donor observations contained in this study's sample. Thus, subsequent estimation results are unlikely to suffer from the biasing influence of an excessive number of itemizers who make small or no contributions. Consequently, tobit is unnecessary.

\textsuperscript{33}Depending on the tax-exempt status of the donee, gifts of appreciated property cannot exceed either 20 or 30 percent of donors' adjusted gross income. Qualifying gifts of appreciated property are then added to all other gifts. The resulting total cannot exceed 50 percent of donors' adjusted gross income. Gifts in excess of these ceilings are carried forward to subsequent years.

\textsuperscript{34}This operationalization excludes carryovers from current contributions. Carryovers arise when donors contributions exceed federally mandated ceilings. Carryovers pose an interesting problem. In the year of origination, carryovers reduce donors' disposable income and force them to wait awhile before they can enjoy the tax benefits of giving, thus increasing the price of giving. However, having to wait may reduce these donors' overall price of giving. When a carryover is triggered, contributions are probably shielding taxable income subject to relatively low marginal tax rates. If they reduce contributions in subsequent years, carryovers could end up shielding taxable income subject to relatively higher marginal tax rates, thus reducing the price of giving. Assessing the impact of carryovers on current giving seems to be an interesting pursuit in and of itself. However, holding convention constant, the intent of this study is to determine whether a dynamic model of giving receives greater statistical, specification, and a prior theoretical support than its static rivals. For this reason, accounting for the effect of carryovers is beyond the scope of this study.

\textsuperscript{35}Consumer Price Indices for all Urban Consumers were obtained from the Consumer Price Index Detailed Report [Bureau of Labor Statistics (1979-1986)]. The indices are as follows: 1979--76.7; 1980--86.3; 1981--94.0; 1982--97.6; 1983--101.3; 1984--105.3; 1985--109.3, and 1986--110.5.

Research Design
is then transformed into its natural-log counterpart to facilitate computation of elasticity estimates.

**Disposable income.** Disposable income is obtained by restating adjusted gross income in 1982 dollars and then subtracting the no-charitable-deduction tax liability.\textsuperscript{36,37}

\textsuperscript{36} Charitable giving, disposable income, and price are simultaneously determined. The resulting threat of simultaneity bias has conventionally been mitigated by introducing first-dollar income and price measures [Feldstein (1975)]. These first-dollar surrogates are obtained by computing taxable income as though there were no charitable deduction.

\textsuperscript{37} Because disposable 'economic' income is defined as personal consumption plus wealth accretion less coerced expenditures, this operationalization is flawed. The flawed nature of this income stems from the way in which the Internal Revenue Code allows donors to compute adjusted gross income (AGI). The formula for AGI permits:

1. Exclusion of several legitimate sources of economic income. These omitted sources of income include 'tax-exempt' (e.g., the long-term portion of capital gains and municipal bond interest) and 'nontaxable' income (e.g., disability and foreign source income and life insurance and certain lawsuit proceeds).

2. Utilization of a variety of 'artificial' deductions (e.g., the two wage-earner and dividends-received deductions) and exclusions (e.g., the all-savers exclusion). The reductions brought about by these deductions and exclusions are artificial in the sense that they reduce donors' disposable income even though donors have had no real decrements in their purchasing power. That is, these deductions and exclusions are not accompanied by either a coerced or discretionary outflow of cash.

3. Utilization of a variety of adjustments to reduce taxpayers reported income. These adjustments typically involve discretionary outflows of cash that either enhance donors' wealth accretion (e.g., IRA and KEOGH plans) or reduce donors' disposable income (e.g., moving expenses and alimony payments).

An ideal operationalization should control for the downward bias that these flaws exert upon disposable income. However, holding convention constant, the intent of this study is to determine whether a dynamic model of giving dominates its rivals on statistical, specification, and a priori theoretical grounds. Thus, evaluating an alternative measure of disposable income is beyond the scope of this study.

**Research Design**
This tax liability also reflects the 1982 price level adjustment. The resulting first-dollar disposable-income measure is then transformed into its natural-log counterpart to facilitate computation of income elasticities.

**Price of giving.** The first-dollar price per dollar of cash or unappreciated (basis equals fair market value) property is traditionally defined as:

$$\text{Price}_{\text{CASH}} = (1 - \text{First-Dollar Marginal Tax Rate})$$  \hspace{1cm} (11)

Price is computed by first identifying donors' no-charitable-contribution tax liabilities. Donors' tax liabilities are then computed under the assumption of a $100 charitable deduction. The first-dollar marginal tax rates are computed by dividing the difference between these two hypothetical liabilities by 100.\(^{38,39,40}\) This computational scheme permits

---

\(^{38}\)Since first-dollar disposable income and price are to a large extent jointly determined by taxable income, it is customary to say something about multicollinearity. Multicollinearity is mitigated by increasing sample size and introducing an exogenous source of price variation. This study's panel-data set excels in both mitigating dimensions. After applying sample selection criteria, the panel data set allows me to track 1,382 taxpayers across eight years, giving a total of 11,056 observations. This large sample helps to separate the unique influences that disposable income and price exert on donors' charitable giving impulse. In addition, the panel covers a period of major tax reform, the Economic Recovery Act of 1981, and stands at the threshold of another, the Tax Reform Act of 1986. The resulting direct and indirect (i.e., via the broadening of income brackets) reduction in tax rates endows price with a statutory source of variation that is independent of the variation in taxable income and thus disposable income. The following presentation of tax rate schedules for married donors who file joint, head of household donors, and single donors highlights the statutory reduction in tax rates:

---

*Research Design* 64
<table>
<thead>
<tr>
<th>MARRIED/Joint**</th>
<th>MARGINAL TAX RATES (NTRS)</th>
<th>MARRIED/Joint NTRS</th>
<th>MARRIED/Joint NTRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>TI ≤ 3.4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3.4 &lt; TI ≤ 5.5</td>
<td>14</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>5.5 &lt; TI ≤ 7.6</td>
<td>16</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>7.6 &lt; TI ≤ 11.9</td>
<td>18</td>
<td>18</td>
<td>18</td>
</tr>
<tr>
<td>11.9 &lt; TI ≤ 16.0</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>16.0 &lt; TI ≤ 20.2</td>
<td>24</td>
<td>24</td>
<td>24</td>
</tr>
<tr>
<td>20.2 &lt; TI ≤ 26.6</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td>26.6 &lt; TI ≤ 32.9</td>
<td>32</td>
<td>32</td>
<td>32</td>
</tr>
<tr>
<td>29.9 &lt; TI ≤ 35.2</td>
<td>37</td>
<td>37</td>
<td>37</td>
</tr>
<tr>
<td>35.2 &lt; TI ≤ 45.8</td>
<td>43</td>
<td>43</td>
<td>43</td>
</tr>
<tr>
<td>45.8 &lt; TI ≤ 50.0</td>
<td>49</td>
<td>49</td>
<td>49</td>
</tr>
<tr>
<td>50.0 &lt; TI ≤ 54.6</td>
<td>54</td>
<td>54</td>
<td>54</td>
</tr>
<tr>
<td>54.6 &lt; TI ≤ 59.6</td>
<td>59</td>
<td>59</td>
<td>59</td>
</tr>
<tr>
<td>59.6 &lt; TI ≤ 64.4</td>
<td>64</td>
<td>64</td>
<td>64</td>
</tr>
<tr>
<td>64.4 &lt; TI ≤ 70.6</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
</tbody>
</table>

*Reduce the tax determined from this schedule by the 1.25% rate reduction credit for 1981.

**This schedule applies to surviving spouses.


<table>
<thead>
<tr>
<th>HEAD OF HOUSEHOLD</th>
<th>MARGINAL TAX RATES (NTRS)</th>
<th>HEAD OF HOUSEHOLD NTRS</th>
<th>HEAD OF HOUSEHOLD NTRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>TI ≤ 2.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2.3 &lt; TI ≤ 4.4</td>
<td>14</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>4.4 &lt; TI ≤ 6.5</td>
<td>18</td>
<td>18</td>
<td>18</td>
</tr>
<tr>
<td>6.5 &lt; TI ≤ 8.7</td>
<td>22</td>
<td>22</td>
<td>22</td>
</tr>
<tr>
<td>8.7 &lt; TI ≤ 11.8</td>
<td>26</td>
<td>26</td>
<td>26</td>
</tr>
<tr>
<td>11.8 &lt; TI ≤ 15.0</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>15.0 &lt; TI ≤ 18.2</td>
<td>34</td>
<td>34</td>
<td>34</td>
</tr>
<tr>
<td>18.2 &lt; TI ≤ 23.5</td>
<td>38</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td>23.5 &lt; TI ≤ 28.3</td>
<td>42</td>
<td>42</td>
<td>42</td>
</tr>
<tr>
<td>28.3 &lt; TI ≤ 34.1</td>
<td>46</td>
<td>46</td>
<td>46</td>
</tr>
<tr>
<td>34.1 &lt; TI ≤ 44.7</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>44.7 &lt; TI ≤ 60.6</td>
<td>54</td>
<td>54</td>
<td>54</td>
</tr>
<tr>
<td>60.6 &lt; TI ≤ 91.8</td>
<td>58</td>
<td>58</td>
<td>58</td>
</tr>
<tr>
<td>91.8 &lt; TI ≤ 126.3</td>
<td>63</td>
<td>63</td>
<td>63</td>
</tr>
<tr>
<td>126.3 &lt; TI ≤ 161.3</td>
<td>68</td>
<td>68</td>
<td>68</td>
</tr>
<tr>
<td>161.3 &lt; TI ≤ 207.4</td>
<td>73</td>
<td>73</td>
<td>73</td>
</tr>
<tr>
<td>207.4 &lt; TI ≤ 256.3</td>
<td>78</td>
<td>78</td>
<td>78</td>
</tr>
<tr>
<td>256.3 &lt; TI ≤ 313.3</td>
<td>83</td>
<td>83</td>
<td>83</td>
</tr>
<tr>
<td>313.3 &lt; TI ≤ 379.3</td>
<td>88</td>
<td>88</td>
<td>88</td>
</tr>
</tbody>
</table>

*Reduce the tax determined from this schedule by the 1.25% rate reduction credit for 1981.


Research Design
<table>
<thead>
<tr>
<th>SINGLE INDIVIDUALS</th>
<th>MARGINAL TAX RATES (MTRS)</th>
<th>SINGLE INDIVIDUALS</th>
<th>MTR'S</th>
<th>SINGLE INDIVIDUALS</th>
<th>MTR'S</th>
</tr>
</thead>
<tbody>
<tr>
<td>TI &lt; 2.3</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>2.3 &lt; TI &lt; 3.4</td>
<td>14</td>
<td>14</td>
<td>14</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>3.4 &lt; TI &lt; 4.4</td>
<td>16</td>
<td>16</td>
<td>16</td>
<td>14</td>
<td>13</td>
</tr>
<tr>
<td>4.4 &lt; TI &lt; 6.5</td>
<td>18</td>
<td>18</td>
<td>18</td>
<td>16</td>
<td>15</td>
</tr>
<tr>
<td>6.5 &lt; TI &lt; 8.5</td>
<td>19</td>
<td>19</td>
<td>19</td>
<td>17</td>
<td>15</td>
</tr>
<tr>
<td>8.5 &lt; TI &lt; 10.8</td>
<td>21</td>
<td>21</td>
<td>21</td>
<td>19</td>
<td>17</td>
</tr>
<tr>
<td>10.8 &lt; TI &lt; 12.9</td>
<td>24</td>
<td>24</td>
<td>24</td>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>12.9 &lt; TI &lt; 15.0</td>
<td>26</td>
<td>26</td>
<td>26</td>
<td>24</td>
<td>22</td>
</tr>
<tr>
<td>15.0 &lt; TI &lt; 18.2</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>27</td>
<td>25</td>
</tr>
<tr>
<td>18.2 &lt; TI &lt; 23.5</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td>31</td>
<td>28</td>
</tr>
<tr>
<td>23.5 &lt; TI &lt; 28.8</td>
<td>39</td>
<td>39</td>
<td>39</td>
<td>36</td>
<td>32</td>
</tr>
<tr>
<td>28.8 &lt; TI &lt; 34.1</td>
<td>44</td>
<td>44</td>
<td>44</td>
<td>40</td>
<td>36</td>
</tr>
<tr>
<td>34.1 &lt; TI &lt; 41.5</td>
<td>49</td>
<td>49</td>
<td>49</td>
<td>46</td>
<td>42</td>
</tr>
<tr>
<td>41.5 &lt; TI &lt; 55.3</td>
<td>55</td>
<td>55</td>
<td>55</td>
<td>52</td>
<td>49</td>
</tr>
<tr>
<td>55.3 &lt; TI &lt; 81.8</td>
<td>65</td>
<td>65</td>
<td>65</td>
<td>61</td>
<td>56</td>
</tr>
<tr>
<td>81.8 &lt; TI &lt; 108.3</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>65</td>
<td>60</td>
</tr>
<tr>
<td>108.3 &lt; TI</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>65</td>
<td>60</td>
</tr>
</tbody>
</table>

*Reduce the tax determined from this schedule by the 1.25% rate reduction credit for 1981.

Tax rates are not shown for married donors who file separately because these donors are dropped from the sample (See Section 3.1.3 (page 77), The sample, for details.

39 By including donors' state marginal tax rates in his definition of price, Feenberg (1987) introduced an additional source of independent variation into his price variable. However, since subsequent econometric estimations generate elasticity estimates having small standard errors, this study's panel-data set is sufficient to mitigate multicollinearity. In addition, holding convention constant, the objective of this study is to determine whether a dynamic model of giving dominates its static rivals on statistical, specification, and a priori theoretical grounds. Consequently, an analysis that includes state marginal tax rates is left for future research.

40 Reece and Zieschang (1989, 1985) implement a theoretically superior alternative to the first-dollar price of giving. Rather than using a single first-dollar price, Reece and Zieschang use the entire schedule of prospective prices to produce maximum-likelihood estimates that properly account for nonlinearity in donors' budget sets. Because this alternative approach is relatively difficult to implement and fairly labor intensive, it has not been widely adopted. For these reasons, the conventional first-dollar price of giving is used in this study.
price measures to fully reflect the sensitivity of donors' tax liability to minor variations in deductibility.

When donors make gifts of appreciated property, an adjustment is made when computing price.\textsuperscript{41} If the alternative to contributing the appreciated property is selling and keeping the net-of-tax proceeds, price becomes:\textsuperscript{42}

\[ P = C(1 - T) + (1 - C)[(1 - T) - (0.50 \times 0.40T)] \]  \hspace{1cm} (12)

C represents each donor's ratio of cash gifts to total gifts. \( T \) and \( 1 - T \) represent the marginal tax rates and the price of cash-only gifts. \( 1 - C \) represents each donor's ratio of appreciated property gifts to total gifts.\textsuperscript{43} The expression

\textsuperscript{41}Tax return data does not permit categorization of donors' property gifts as gifts of appreciated or unappreciated property. Thus, noncash gifts have traditionally been treated as gifts of appreciated property. The legitimacy of this assumption is discussed in footnote 44 (page 68).

\textsuperscript{42}If selling is the alternative to donating, the following example shows why appreciated property plays an important role in some donors' giving strategies. Suppose two donors are identical except in the composition of their $5,000 gifts. Donor A's $5,000 gift is composed solely of cash. Donor B's $5,000 gift is composed of $1,500 cash and $3,500 appreciated property. With a marginal tax rate of 0.35, Donor A and B's prices are $0.65 \((1 - 0.35)\) and $0.60 \(((1,500 / 5,000) \times (1 - 0.35)) + (1 - (1,500 / 5,000)) \times [(1 - 0.35) - (0.50 \times (0.40 \times 0.35))]\), respectively. Thus, exploitation of the price-reducing influence of long-term capital gains reduces donor B's price by 5 cents on the dollar.

\textsuperscript{43}The ratio of cash gifts to total gifts and appreciated property gifts to total gifts is dependent upon donors' realized gifts. This dependency imposes a degree of endogeneity upon the price measures of donors whose portfolio of contributions consist solely or partially of appreciated property [O'Neil, Steinberg, and Thompson (1990)]. Although assessing the biasing influence of this endogeneity is a worthwhile exercise, it is beyond the narrowly defined scope of this study. For this reason, this issue is left for future research.

Research Design

67
[(1 - T) - (0.50 * 0.40T)] represents the capital-gains tax rates for gifts of appreciated property. The appreciation ratio of 0.50 reflects the conventional assumption about the ratio of asset appreciation to market value for gifts of appreciated property. The taxation ratio, 0.40, reflects the percentage of long-term capital gains (i.e., appreciation).

44 Little is known about donors' actual appreciation ratios. What is known has its genesis in work by Feldstein and Clotfelter (1976) and Auten and Rudney (1986). Using a maximum-likelihood procedure, Feldstein and Clotfelter found that even though the likelihood function was relatively flat between ratios of 0.25 and 0.75, it did obtain a maximum at 0.50. Auten and Rudney show that for the years 1971-1975, donors having $200,000 to $500,000 in adjusted gross income (AGI) had appreciation ratios of 0.51. Donors with AGI in excess of $500,000 had appreciation ratios of 0.71.

Because less than one-half of one percent of this study's donor observations reflect adjusted gross incomes in excess of $200,000, these appreciation ratios seem to have limited applicability to this study. An examination of donors' charitable contributions strengthens the credibility of this argument:

35% of donor observations (3,870 out of 11,056) reflect gifts comprised solely of cash.
47% of donor observations (5,196 out of 11,056) reflect property gifts less than $500.
18% of donor observations (1,990 out of 11,056) reflect property gifts greater than or equal to $500.

*A breakpoint of $500 was chosen because the Internal Revenue Service legitimizes gifts greater than or equal to $500 by requiring donors to report the donees, fair-market values, and methods of appraisal.

Long-term capital gains probably account for little, if any, of the fair market value of small (less than $500) property gifts. By implication, small property gifts are essentially cash contributions in disguise. If this is true, an appreciation ratio of zero (no appreciation) is appropriate for 82 percent of donor observations (those observations reflecting cash-only and small property gifts). However, because the intent of this study is to determine whether dynamic models dominates rivals, holding all other aspects of convention constant, exploration of this appreciation ratio issue is beyond the scope of this study.

Research Design
subject to taxation.

**Demographic characteristics.** By convention and to proxy for differences in donors' utility functions, a set of demographic variables is added to this study's static and dynamic models of giving. These variables indicate whether changes in donors' marital status, number of dependents, and age influence this year's contributions. Marital status is determined by donors' filing status. If donors' filing status is either married-filing-joint or qualifying widows(ers), the marital-status dummy variable takes on a value of one.\(^45\) The marital-status dummy variable takes on a value of zero if donors' filing status is either single or head-of-household.\(^46\) The number of dependents is a multichotomous ordinal variable and is determined by summing across 'exemptions for children living at and away from home'. Tax returns provide little information about donors' ages. Returns only reveal whether an old-age exemption was taken. Consequently, the age dummy variable takes on a value of one if an old-age exemption is taken and zero otherwise.

\(^45\)Sample-selection procedures systematically eliminate married taxpayers who file separately. See Section 3.1.3 (page 77), *The sample*, for a justification of this sample-selection procedure.

\(^46\)Head of household donors were put with single rather than married donors in order to be consistent with Daniel's classification scheme. In this study, head of household observations total 537, or 4.8% of the sample (see Table 3.2 (page 83) for details).
3.1.1.2 Surrogates for 'new' elasticity constructs.

Operational counterparts are needed for the 'new' elasticity constructs motivated by consumer theory's habit persistence and life cycle arguments. Lagged contributions serve as surrogates for the influence that last year's giving patterns exert upon this year's giving when donors' learning about tax changes takes place with a delay.\footnote{If correlated with this year's error term, Broman and others argue that the use of lagged contributions as an explanatory variable may cause inconsistent parameter estimates. Despite this potential difficulty, lagged contributions are used in this study because:}

1. Last year's contributions are predetermined when this year's gift is made. Consequently, there is no a priori reason to believe last year's gifts will be correlated with this year's error term.

2. Using fitted or predicted values of last year's contributions from the static two-way fixed-effects model as an instrumental variable for lagged contributions, the instrumental variable model generates parameter estimates which are statistically identical ($P < 0.01$) to those generated by models using lagged contributions. The parameter estimates of the dynamic two-way fixed-effects model are shown, with and without an instrumental variable for lagged contributions, because this model dominates its static and dynamic rivals on statistical specification, and a priori grounds.

---

\footnote{If correlated with this year's error term, Broman and others argue that the use of lagged contributions as an explanatory variable may cause inconsistent parameter estimates. Despite this potential difficulty, lagged contributions are used in this study because:}

With Instrumental Variable for Lagged Contributions:

\[
\text{Contributions} = 0.1507 + 0.2167 \text{LAGCON} + 0.1235 \text{LAGINC} + \\
0.3832 \text{LAGPRC} + 0.2048 \text{LOGINC} - \\
1.1118 \text{LOGPRC} + 0.5041 \text{MARDUM} + \\
0.0167 \text{AGEDUM} - 0.0099 \text{NUMDEP} + \\
0.0823 \text{LEDINC} + 0.5249 \text{LEDPRC}
\]

Without Instrumental Variable for Lagged Contributions:

\[
\text{Contributions} = 0.3747 + 0.1556 \text{LAGCON} + 0.1571 \text{LAGINC} + \\
0.3543 \text{LAGPRC} + 0.1873 \text{LOGINC} - \\
1.1808 \text{LOGPRC} + 0.5138 \text{MARDUM} + \\
0.0147 \text{AGEDUM} - 0.0076 \text{NUMDEP} + \\
0.0731 \text{LEDINC} + 0.4280 \text{LEDPRC}
\]
lagged disposable income and price serve as surrogates for the influence that last year’s disposable income and last year’s price of giving exert upon this year’s giving. Assuming that donors form fully rational expectations about next year’s disposable income and price of giving, lead variables on disposable income and price serve as surrogates for the influence that next year’s disposable income and next year’s

Using the instrumental variable model as the point of reference, the following two-sided t test statistics indicate that the parameter estimates of the model without the instrumental variable are statistically equivalent to their counterparts in the model with the instrumental variable for lagged contributions:

<table>
<thead>
<tr>
<th>Instrument Status</th>
<th>LAGCON</th>
<th>LAGINC</th>
<th>LAGPRC</th>
<th>LOGINC</th>
<th>LOGPRC</th>
<th>LEDINC</th>
<th>LEDPRC</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Standard Errors</td>
<td>0.2167</td>
<td>0.1235</td>
<td>0.3832</td>
<td>0.2048</td>
<td>-1.1118</td>
<td>0.0823</td>
<td>0.5249</td>
</tr>
<tr>
<td>Without</td>
<td>0.1274</td>
<td>0.0682</td>
<td>0.1437</td>
<td>0.0442</td>
<td>0.1172</td>
<td>0.0408</td>
<td>0.1227</td>
</tr>
<tr>
<td>t Test Statistic</td>
<td>0.48*</td>
<td>-0.49</td>
<td>0.20</td>
<td>0.40</td>
<td>0.59</td>
<td>0.23</td>
<td>0.79</td>
</tr>
<tr>
<td>(6,895 degrees of freedom)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Conclusion:**

Parameters are: Equal Equal Equal Equal Equal Equal Equal

*Using the elasticity estimates associated with last year’s giving to illustrate, each t test statistic is formatted as follows:

\[
\frac{0.2167 - 0.1556}{0.2167} = 0.48_{6895}
\]

**Unless one is willing to accept P values greater than 20 percent, these alternative sets of elasticity estimates are statistically and interpretationally identical.

Research Design

71
price of giving exert upon this year's giving.\textsuperscript{48}

3.1.2 The tax calculator.

Numerical values for each operational variable are generated by REVTAX. REVTAX is a revised and extended version (REV) of Daniel's (1989) tax calculator (hereafter DANTAX). Using DANTAX coding helps ensure differences in parameter estimates are attributable to advances in data collection, econometric modeling, and/or estimation algorithms rather than disparity between tax calculators.

DANTAX's collection of SAS macros focuses primarily upon the tax-computation provisions of the Internal Revenue Code for the years 1979 through 1984. Consequently, DANTAX includes applicable rate schedules, alternative tax-computation algorithms (e.g., the maximum tax for years 1979 through 1981, alternative-maximum tax for 1981, and income-averaging tax for years 1979 through 1984), and additional taxes. These macros also reflect the changing complexion of credits during the 1979 to 1984 time period. Credits include

\textsuperscript{48}Assuming donors form fully rational expectations means that on average donors are able to correctly divine next year's income and price. Thus, next year's actual disposable income and price provide reasonable surrogates for donors' expectations about next year's income and price. Please note however that realized future prices and income depart randomly from the forecast values which determine behavior. Thus, the resulting measurement error biases the coefficients on lead variables, presumably towards zero.

Research Design 72
the elderly, child care, investment, energy, foreign tax, WIN, and JOBS credits. DANTAX's SAS macros also take into account other-tax provisions such as the alternative minimum, self-employment, minimum, and IRA taxes, social security tax on tips, and prior-year investment and advanced earned income credits.

The primary programming objective of DANTAX is the creation of first-dollar disposable-income and price-of-giving data. Using tax-return data, DANTAX recomputes taxable income as though no charitable deduction were allowed.\textsuperscript{49} Depending on donors' tax scenarios, the operational elimination of the charitable deduction modifies, activates, and/or deactivates rate schedules and/or other tax-computation algorithms. An ideal tax calculator should consider each of these possibilities. Although able to effectively deal with modification and deactivation tendencies, DANTAX fails to consider activation tendencies. This anomaly has an interesting implication. Without considering the possible activation of each potential tax-computation algorithm, DANTAX may generate local rather than global minimizations of donors

\textsuperscript{49}Except for restating in terms of 1982 dollars, the recomputation of taxable income leaves each donor's original tax-return computation of adjusted gross income and 'other' itemized deductions intact. This implies the original ceilings and floors limiting itemized deductions continue to apply. Thus, there is no need for DANTAX to recompute a donor's other itemized deductions.
tax liabilities.\footnote{An example is the best way to illustrate this implication. Suppose the income-averaging algorithm generates a donor's original least-cost tax liability. Elimination of this donor's charitable deduction results in a larger taxable income, thus causing the rate-schedule and income-averaging algorithms to generate larger tax liabilities. If the new income-averaging tax liability is less than the new rate-schedule tax liability, the income-averaging algorithm is retained. In this case, the utilization of the income-averaging algorithm is simply modified. Had the new income-averaging tax liability exceeded the new rate-schedule tax liability, the new rate-schedule tax liability would have been selected, thus deactivating the income-averaging algorithm. The retention of the income-averaging algorithm in the modification scenario is somewhat myopic. Even though the modified income-averaging tax liability is less than the modified rate-schedule liability, the income-averaging liability may actually exceed the tax liability generated by some other alternative tax-computation algorithms had they been considered. The same possibility exists in the deactivation scenario. In other words, ignoring the potential activation of all competing tax-computations algorithms may result in a local rather than a global minimization of donors' tax liability.} 

However, several mitigating factors should lessen the reader's concern over whether donors' tax liabilities are minimized when the deduction is operationally eliminated. First, donors' original tax-minimizing algorithms are probably not very sensitive to minor differences among alternative tax-computation algorithms. Second, the conventional sample-selection strategy of eliminating borderline itemizers purges this study's sample of donors whose tax minimizations are overly sensitive to charitable contributions.\footnote{Borderline itemizers are those donors whose ability to itemize is contingent upon the size of their charitable contributions. Additional justification for the elimination of this particular group of donors appears in Section 3.1.3, (page 77) The sample.} Third, nearly

Research Design
90 percent of all original tax-return liabilities are generated by the regular rate-schedule algorithm. This suggests that alternative tax-computation algorithms are not very important to the donors found in this study's sample.\textsuperscript{52}

Fourth, the timing and amount of contributions are at least partially conditioned upon donors' original charitable-contribution tax-computation status. Introducing a new tax-computation algorithm may place donors in artificial giving environments which no longer elicit original responses to taxation. Finally, in most cases the information needed for alternative tax-computation algorithms is not available.\textsuperscript{53}

\textsuperscript{52}The following frequency distribution provides a summary of the original tax-computation algorithms used by the donors in this sample:

<table>
<thead>
<tr>
<th>Tax-Computation Method</th>
<th>Frequency</th>
<th>Percent</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular Tax</td>
<td>9,597</td>
<td>86.8</td>
<td>9,597</td>
<td>86.8</td>
</tr>
<tr>
<td>Alternative Minimum Tax</td>
<td>1,046</td>
<td>9.5</td>
<td>10,643</td>
<td>96.3</td>
</tr>
<tr>
<td>Income Averaging Tax</td>
<td>171</td>
<td>1.5</td>
<td>10,814</td>
<td>97.8</td>
</tr>
<tr>
<td>No Tax</td>
<td>117</td>
<td>1.1</td>
<td>10,931</td>
<td>98.9</td>
</tr>
<tr>
<td>Regular Maximum Tax</td>
<td>110</td>
<td>1.0</td>
<td>11,041</td>
<td>99.9</td>
</tr>
<tr>
<td>Partially Tax Exempt/Regular Tax</td>
<td>7</td>
<td>0.1</td>
<td>11,048</td>
<td>99.9</td>
</tr>
<tr>
<td>Partially Tax Exempt/Alt. Tax</td>
<td>7</td>
<td>0.1</td>
<td>11,055</td>
<td>100.0</td>
</tr>
<tr>
<td>Alternative Maximum Tax Computation</td>
<td>1</td>
<td>0.0</td>
<td>11,056</td>
<td>100.0</td>
</tr>
</tbody>
</table>

This descriptive information suggests that only about 10 percent (1,459 out of 11,056) of the total observations in this study's sample reflect the use original tax-computation algorithms other than the regular rate-schedule algorithm.

\textsuperscript{53}For example, if either the maximum or alternative-maximum tax algorithm were activated, the lack of personal-service income information prevents computation of revised tax liabilities under either algorithm.

Research Design
Because these arguments mitigate concern over the activation of previously unused tax-computation algorithms, REVTAX does not consider activation tendencies. If these mitigating factors prove ineffectual, the use of DANTAX in creating REVTAX is a limitation of this study.

Publication X [Internal Revenue Service (1979-1986)] and U.S. Master Tax Guides [Commerce Clearing house (1979-1986)] are used to verify DANTAX's SAS macros. The process of verification results in the following minor revisions to DANTAX's original program code:

1. Errors in rate-schedule income brackets and marginal tax rates are corrected.

2. Coding is added to allow qualifying donors to take credits against 1981 and 1982's alternative-minimum tax liabilities.

3. Computation of modified income-averaging tax liabilities requires recomputation of donors' base-period incomes. For years prior to 1983, there is not enough information in the panel to compute the four-year-average base-period incomes required by the tax code. To get around this difficulty, DANTAX uses an iterative algorithm to generate reasonable approximations of pre-1983 base-period incomes. For years subsequent to 1982, the tax code requires donors to use three-year-average base-period incomes when income averaging. Because the panel has enough information to compute the three-year-average base-period incomes, coding is added to allow REVTAX to use this information rather than the iterative algorithm.

4. Coding is added to compute the advanced earned income credit for years after 1981.
5. Coding is added to ensure contribution deductions do not exceed federally mandated ceilings.\textsuperscript{54}

6. Disposable income is redefined as adjusted gross income less the no-charitable-deduction tax.\textsuperscript{55}

7. Coding is added to restate contributions and adjusted gross income, and thus disposable income and price, in terms of 1982 dollars.

DANTAX's revised program coding is extended to reflect relevant Code provisions for 1985 and 1986. The revised and extended program coding form REVTAX.

3.1.3 The sample.

In 1979, the Statistics of Income Division of the Internal Revenue Service randomly selected five different four-digit Social-Security-Number (SSN) endings to facilitate creation of an ongoing panel of taxpayers. Each taxpayer having one of these four-digit SSN endings was to appear in

\textsuperscript{54} When in excess of mandated ceilings (see footnote 31 (page 61) for details), contributions are limited to the total deductible contributions reported on donors' tax returns. Prior to being used as ceilings, these totals have been restated in terms of 1982 dollars. Excess contributions are treated as carryovers (see footnote 32 (page 62) for details).

\textsuperscript{55} Daniel defines disposable income as adjusted gross income minus the no-charitable-deduction tax plus individual retirement account payments. This definition reflects Daniel's attempt to identify a measure of disposable income that is more in harmony with its economic counterpart. However, as argued in footnote 37 (page 63), the best tax-return measure of economic disposable income requires considerably more than an adjustment for individual retirement account payments. Consequently, Daniel's definition of disposable income is abandoned in favor of this conventional one.
every year covered by the panel. However, as shown in Figure 3.1, after just three years, taxpayers having the four-digit endings C, D, E were dropped. Only taxpayers having either four-digit ending A or B were retained in the panel after 1981. Worse still, only those donors having the four-digit

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>5,786</td>
</tr>
<tr>
<td>B</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>** Returns Per Year **</td>
<td>45141</td>
<td>46214</td>
<td>46670</td>
<td>9235</td>
<td>19120</td>
<td>9762</td>
<td>20202</td>
<td>10120</td>
<td></td>
</tr>
</tbody>
</table>

** Indicates that taxpayers having this particular four-digit SSN ending appeared in the panel for the year indicated.

FIGURE 3.1 PANEL SAMPLE CONFIGURATION

Social Security Number ending of 'A' appear in each of the years covered by the panel.

In keeping with convention, only taxpayers appearing in every panel year are used in this study. This initial subset of 5,786 taxpayers is called the balanced panel. Over 200 fields of tax-return information accompanies each appearance of a given taxpayer in the panel. The balanced panel is further reduced by the following conventional sample-selection criteria:

56 The balanced panel omits returns not appearing in every year. This process may introduce attrition bias into parameter estimates [Christian and Frischmann (1989)].
1. No late filers are included.57

2. Tax returns typically provide no insight into nonitemizers' charitable giving. This lack of information is due to the nondeductibility of nonitemizers' contributions. For this reason, taxpayers who did not itemize in every panel year are excluded.58

3. Some donors qualify as itemizers only when they make substantial charitable contributions. The first-dollar price of these donors is one dollar. This price is not reflective of the actual price of giving for these donors [Clotfelter (1980)]. For this reason, these 'endogenous' or borderline itemizers are eliminated from the sample.

4. When a married couple files separate tax returns, the high-bracket spouse usually declares the contributions. This means the return of the low-bracket spouse contains misleading contribution and price-of-giving information. In addition, the tax return of the high-bracket spouse understates the couple's total disposable income. Consequently, separate filers are eliminated from the sample.

5. Some donors report negative adjusted-gross income. Because natural-log counterparts do not exist for negative disposable income values and their related marginal tax rates, the log-linear functional form

57 Per documentation accompanying the balanced-panel tape.

58 As the only exception, the 1981 to 1986 portion of the panel used in this study contains data on the charitable giving of nonitemizing donors. During this time period, policymakers granted deductibility status to nonitemizers' charitable contributions. However, from 1981 through 1984, extremely restrictive ceilings permitted deductibility to reach only a trivial portion of nonitemizers' charitable contributions and rendered any price reduction inframarginal. Consequently, data from these years provides very little insight into nonitemizers' charitable giving. In 1985, nonitemizers were allowed to deduct up to 50 percent of their charitable contributions. In 1986, deductibility was extended to 100 percent of nonitemizers' charitable contributions. Thus, at best, this panel only contains two years of meaningful data on the contributions of nonitemizers. For this reason, an examination of the charitable-giving activities of nonitemizers is beyond the scope of this study.
is rendered unsuitable. In order to retain the log-linear functional form, these donors are eliminated from the balanced panel.

6. Some taxpayers having four-digit SSN endings other than A were erroneously included in the balanced panel. Nearly all of these taxpayers are high-income taxpayers. These high-income outliers are eliminated from the sample.

Elimination of these taxpayers reduces the panel to 1,382 donors. Since each donor appears every year, the sample has 11,056 (1382 donors * 8 years) observations. This restricted panel is basically a random sample of middle-class itemizing donors.

To provide the reader with additional insight into the information contained in this restricted panel, Tables 3.1 and 3.2 provide descriptive statistics for each of the variables that are of interest to this study. These Tables permit readers to contrast raw tax return measures with those generated by REVITAX. In addition, Table 3.2 contains frequency information on donors' marital status, age, and dependents. Raw tax return data suggests that the mean (median) donor:

---

59 Per private conversation with Charles Christian at the American Taxation Association's mid-year meeting at Albuquerque, New Mexico, February 14, 1991.

60 Ninety percent of the observations in this sample are from donors whose adjusted gross incomes (tax return) are between 14,617 and 92,930 dollars. The corresponding amounts in 1982 dollars are 15,204 and 92,354. Comparable tax-return and first-dollar disposable income amounts are 13,579 and 70,800 and 14,100 and 68,497, respectively.
### Table 3.1 Descriptive Statistics for Adjusted Gross Income, Disposable Income, and Price

#### Adjusted Gross Income (Tax Returns)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>34,118</td>
<td>28,567</td>
<td>2,647—448,378</td>
<td>20,775</td>
</tr>
<tr>
<td>1980</td>
<td>35,195</td>
<td>31,958</td>
<td>3,826—836,204</td>
<td>37,102</td>
</tr>
<tr>
<td>1981</td>
<td>42,002</td>
<td>34,670</td>
<td>1,071—738,000</td>
<td>40,998</td>
</tr>
<tr>
<td>1982</td>
<td>43,391</td>
<td>36,485</td>
<td>1,346—566,400</td>
<td>35,647</td>
</tr>
<tr>
<td>1983</td>
<td>45,374</td>
<td>38,100</td>
<td>2,675—677,200</td>
<td>40,555</td>
</tr>
<tr>
<td>1984</td>
<td>48,253</td>
<td>40,670</td>
<td>1,981—894,450</td>
<td>42,201</td>
</tr>
<tr>
<td>1985</td>
<td>51,250</td>
<td>42,837</td>
<td>2,451—741,004</td>
<td>42,922</td>
</tr>
<tr>
<td>1986</td>
<td>55,766</td>
<td>44,525</td>
<td>1,115—1,281,000</td>
<td>71,895</td>
</tr>
<tr>
<td>All Yrs</td>
<td>44,919</td>
<td>36,750</td>
<td>1,071—1,281,000</td>
<td>44,591</td>
</tr>
</tbody>
</table>

#### Adjusted Gross Income (1982 Dollars-RevTAX)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>44,423</td>
<td>37,244</td>
<td>3,451—584,587</td>
<td>37,516</td>
</tr>
<tr>
<td>1980</td>
<td>44,258</td>
<td>37,031</td>
<td>4,433—968,150</td>
<td>42,992</td>
</tr>
<tr>
<td>1981</td>
<td>44,683</td>
<td>36,893</td>
<td>1,139—795,106</td>
<td>45,615</td>
</tr>
<tr>
<td>1982</td>
<td>44,457</td>
<td>37,382</td>
<td>1,379—580,328</td>
<td>36,524</td>
</tr>
<tr>
<td>1983</td>
<td>44,792</td>
<td>37,611</td>
<td>2,641—668,509</td>
<td>39,541</td>
</tr>
<tr>
<td>1984</td>
<td>45,824</td>
<td>38,625</td>
<td>1,881—849,478</td>
<td>40,077</td>
</tr>
<tr>
<td>1985</td>
<td>46,889</td>
<td>39,192</td>
<td>2,262—677,954</td>
<td>39,270</td>
</tr>
<tr>
<td>1986</td>
<td>51,372</td>
<td>40,594</td>
<td>1,009—1,159,276</td>
<td>65,061</td>
</tr>
<tr>
<td>All Yrs</td>
<td>45,845</td>
<td>37,593</td>
<td>1,009—1,159,276</td>
<td>43,971</td>
</tr>
</tbody>
</table>

#### Last-Dollar Disposable Income (Tax Returns)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>27,802</td>
<td>24,719</td>
<td>936—306,411</td>
<td>17,312</td>
</tr>
<tr>
<td>1980</td>
<td>30,680</td>
<td>27,376</td>
<td>3,826—528,888</td>
<td>22,229</td>
</tr>
<tr>
<td>1981</td>
<td>33,456</td>
<td>29,519</td>
<td>1,071—411,280</td>
<td>24,364</td>
</tr>
<tr>
<td>1982</td>
<td>35,363</td>
<td>31,489</td>
<td>1,228—339,067</td>
<td>23,161</td>
</tr>
<tr>
<td>1983</td>
<td>37,464</td>
<td>33,010</td>
<td>2,675—427,800</td>
<td>26,663</td>
</tr>
<tr>
<td>1984</td>
<td>39,932</td>
<td>35,366</td>
<td>1,922—506,800</td>
<td>27,418</td>
</tr>
<tr>
<td>1985</td>
<td>42,434</td>
<td>37,125</td>
<td>2,197—444,945</td>
<td>29,008</td>
</tr>
<tr>
<td>1986</td>
<td>45,851</td>
<td>38,803</td>
<td>1,115—741,100</td>
<td>44,425</td>
</tr>
<tr>
<td>All Yrs</td>
<td>36,620</td>
<td>31,579</td>
<td>936—741,100</td>
<td>28,398</td>
</tr>
</tbody>
</table>

#### First-Dollar Disposable Income (Per RevTAX)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>34,272</td>
<td>30,765</td>
<td>3,451—368,217</td>
<td>20,492</td>
</tr>
<tr>
<td>1980</td>
<td>34,246</td>
<td>30,584</td>
<td>4,433—587,997</td>
<td>24,236</td>
</tr>
<tr>
<td>1981</td>
<td>34,766</td>
<td>30,887</td>
<td>1,139—428,136</td>
<td>24,721</td>
</tr>
<tr>
<td>1982</td>
<td>35,717</td>
<td>31,914</td>
<td>2,611—330,304</td>
<td>22,797</td>
</tr>
<tr>
<td>1983</td>
<td>36,562</td>
<td>32,509</td>
<td>2,463—417,861</td>
<td>25,375</td>
</tr>
<tr>
<td>1984</td>
<td>37,727</td>
<td>33,640</td>
<td>1,720—455,243</td>
<td>25,373</td>
</tr>
<tr>
<td>1985</td>
<td>38,732</td>
<td>34,017</td>
<td>1,988—390,743</td>
<td>25,811</td>
</tr>
<tr>
<td>1986</td>
<td>36,170</td>
<td>35,300</td>
<td>1,009—415,122</td>
<td>30,666</td>
</tr>
<tr>
<td>All Yrs</td>
<td>36,680</td>
<td>32,231</td>
<td>1,009—615,122</td>
<td>26,541</td>
</tr>
</tbody>
</table>

#### Last-Dollar Price of Giving (Tax Returns)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>0.6947</td>
<td>0.72</td>
<td>0.2616—1.0</td>
<td>0.1126</td>
</tr>
<tr>
<td>1980</td>
<td>0.6756</td>
<td>0.68</td>
<td>0.2173—1.0</td>
<td>0.1183</td>
</tr>
<tr>
<td>1981</td>
<td>0.6586</td>
<td>0.68</td>
<td>0.2652—1.0</td>
<td>0.1203</td>
</tr>
<tr>
<td>1982</td>
<td>0.6672</td>
<td>0.7082</td>
<td>0.4092—1.0</td>
<td>0.1064</td>
</tr>
<tr>
<td>1983</td>
<td>0.7009</td>
<td>0.709</td>
<td>0.4289—1.0</td>
<td>0.1041</td>
</tr>
<tr>
<td>1984</td>
<td>0.7148</td>
<td>0.72</td>
<td>0.4277—1.0</td>
<td>0.1019</td>
</tr>
<tr>
<td>1985</td>
<td>0.7122</td>
<td>0.72</td>
<td>0.4149—1.0</td>
<td>0.1021</td>
</tr>
<tr>
<td>1986</td>
<td>0.7252</td>
<td>0.7323</td>
<td>0.4000—1.0</td>
<td>0.1059</td>
</tr>
<tr>
<td>All Yrs</td>
<td>0.6972</td>
<td>0.71</td>
<td>0.2173—1.0</td>
<td>0.1112</td>
</tr>
</tbody>
</table>

#### First-Dollar Price of Giving (Per RevTAX)

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Range</th>
<th>StdDev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>0.6423</td>
<td>0.6513</td>
<td>0.2761—1.0</td>
<td>0.1110</td>
</tr>
<tr>
<td>1980</td>
<td>0.6534</td>
<td>0.6737</td>
<td>0.2993—1.0</td>
<td>0.1125</td>
</tr>
<tr>
<td>1981</td>
<td>0.6567</td>
<td>0.6781</td>
<td>0.3000—1.0</td>
<td>0.1120</td>
</tr>
<tr>
<td>1982</td>
<td>0.6836</td>
<td>0.6905</td>
<td>0.4039—1.0</td>
<td>0.1044</td>
</tr>
<tr>
<td>1983</td>
<td>0.7029</td>
<td>0.70</td>
<td>0.4257—1.0</td>
<td>0.1052</td>
</tr>
<tr>
<td>1984</td>
<td>0.7217</td>
<td>0.72</td>
<td>0.4277—1.0</td>
<td>0.1039</td>
</tr>
<tr>
<td>1985</td>
<td>0.7268</td>
<td>0.7375</td>
<td>0.4149—1.0</td>
<td>0.1015</td>
</tr>
<tr>
<td>1986</td>
<td>0.7259</td>
<td>0.7383</td>
<td>0.4000—1.0</td>
<td>0.1050</td>
</tr>
<tr>
<td>All Yrs</td>
<td>0.6897</td>
<td>0.7383</td>
<td>0.4000—1.0</td>
<td>0.1119</td>
</tr>
</tbody>
</table>
1. Has an adjusted gross income of $44,919 ($36,750).

2. Has a last-dollar disposable income (adjusted gross income minus taxes) of $36,620 ($31,579).

3. Has a last-dollar marginal tax rate of 0.3028 (0.2900) with a corresponding last-dollar price of giving of $0.6972 ($0.7100).

4. Makes annual charitable contributions totaling $1,186 ($570).

5. Is married, not 'old', and has one dependent.

By way of contrast, after restating the raw tax return data in terms of 1982 dollars and then computing first-dollar price and income measures, selected data generated by REVSTAX suggests that the mean (median) donor:

1. Has an adjusted gross income, restated in terms of 1982 dollars, of $45,845 ($37,953).


3. Has a first-dollar marginal tax rate of 0.3103 (0.2617) with a corresponding first-dollar price of giving of $0.6897 ($0.7383).

4. Makes annual charitable contributions totaling $1,180 ($587).

5. Is married, not 'old', and has one dependent.

3.2 Research Hypotheses.

The dynamic two-way fixed-effects model of giving is specified as follows:

Research Design
### Table 3.2: Descriptive Statistics for Charitable Contributions, Marital Status, Age, and Dependents

#### Contributions Allowed (per Tax Returns)

<table>
<thead>
<tr>
<th>YEAR</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>RANGE</th>
<th>STDEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>741</td>
<td>362</td>
<td>0–34,198</td>
<td>1,679</td>
</tr>
<tr>
<td>1980</td>
<td>851</td>
<td>433</td>
<td>0–34,779</td>
<td>1,869</td>
</tr>
<tr>
<td>1981</td>
<td>1,030</td>
<td>508</td>
<td>0–49,440</td>
<td>2,486</td>
</tr>
<tr>
<td>1982</td>
<td>1,079</td>
<td>566</td>
<td>0–50,400</td>
<td>2,460</td>
</tr>
<tr>
<td>1983</td>
<td>1,238</td>
<td>631</td>
<td>0–89,230</td>
<td>3,407</td>
</tr>
<tr>
<td>1984</td>
<td>1,292</td>
<td>661</td>
<td>0–57,360</td>
<td>2,834</td>
</tr>
<tr>
<td>1985</td>
<td>1,407</td>
<td>720</td>
<td>0–60,484</td>
<td>3,150</td>
</tr>
<tr>
<td>1986</td>
<td>1,853</td>
<td>792</td>
<td>0–324,100</td>
<td>10,049</td>
</tr>
<tr>
<td>ALLYRS</td>
<td>1,186</td>
<td>570</td>
<td>0–324,100</td>
<td>4,328</td>
</tr>
</tbody>
</table>

#### Charitable Contributions (per REV tax)

<table>
<thead>
<tr>
<th>YEAR</th>
<th>MEAN</th>
<th>MEDIAN</th>
<th>RANGE</th>
<th>STDEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979</td>
<td>953</td>
<td>498</td>
<td>0–44,586</td>
<td>2,138</td>
</tr>
<tr>
<td>1980</td>
<td>958</td>
<td>502</td>
<td>0–37,321</td>
<td>1,889</td>
</tr>
<tr>
<td>1981</td>
<td>1,091</td>
<td>540</td>
<td>0–52,596</td>
<td>2,619</td>
</tr>
<tr>
<td>1982</td>
<td>1,083</td>
<td>576</td>
<td>0–51,701</td>
<td>2,304</td>
</tr>
<tr>
<td>1983</td>
<td>1,219</td>
<td>622</td>
<td>0–88,085</td>
<td>3,363</td>
</tr>
<tr>
<td>1984</td>
<td>1,221</td>
<td>627</td>
<td>0–54,463</td>
<td>2,687</td>
</tr>
<tr>
<td>1985</td>
<td>1,250</td>
<td>658</td>
<td>0–55,338</td>
<td>2,525</td>
</tr>
<tr>
<td>1986</td>
<td>1,672</td>
<td>715</td>
<td>0–293,285</td>
<td>9,092</td>
</tr>
<tr>
<td>ALLYRS</td>
<td>1,180</td>
<td>587</td>
<td>0–293,285</td>
<td>4,003</td>
</tr>
</tbody>
</table>

#### Marital Status

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Single</td>
<td>135</td>
<td>134</td>
<td>134</td>
<td>126</td>
<td>128</td>
<td>133</td>
<td>137</td>
<td>140</td>
<td>1,057</td>
<td>9.7</td>
</tr>
<tr>
<td>Married Filing Joint</td>
<td>1,174</td>
<td>1,176</td>
<td>1,182</td>
<td>1,189</td>
<td>1,185</td>
<td>1,184</td>
<td>1,183</td>
<td>1,175</td>
<td>9,449</td>
<td>85.5</td>
</tr>
<tr>
<td>Head of Household</td>
<td>75</td>
<td>72</td>
<td>66</td>
<td>68</td>
<td>70</td>
<td>65</td>
<td>61</td>
<td>62</td>
<td>537</td>
<td>4.8</td>
</tr>
<tr>
<td>Surviving Spouse</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>0.0</td>
</tr>
</tbody>
</table>

#### Age (Exemption Status)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular Exemptions</td>
<td>1,330</td>
<td>1,325</td>
<td>1,311</td>
<td>1,296</td>
<td>1,279</td>
<td>1,270</td>
<td>1,257</td>
<td>1,240</td>
<td>10,306</td>
<td>93.2</td>
</tr>
<tr>
<td>Old Age Exemptions</td>
<td>52</td>
<td>59</td>
<td>71</td>
<td>86</td>
<td>103</td>
<td>112</td>
<td>125</td>
<td>142</td>
<td>750</td>
<td>6.8</td>
</tr>
</tbody>
</table>

#### Number of Dependents

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Dependents Claimed</td>
<td>422</td>
<td>430</td>
<td>438</td>
<td>453</td>
<td>473</td>
<td>488</td>
<td>520</td>
<td>565</td>
<td>3,789</td>
<td>34.3</td>
</tr>
<tr>
<td>1 Dependent Claimed</td>
<td>291</td>
<td>282</td>
<td>275</td>
<td>268</td>
<td>257</td>
<td>261</td>
<td>258</td>
<td>242</td>
<td>2,134</td>
<td>19.3</td>
</tr>
<tr>
<td>2 Dependents Claimed</td>
<td>390</td>
<td>395</td>
<td>408</td>
<td>418</td>
<td>426</td>
<td>422</td>
<td>404</td>
<td>392</td>
<td>3,253</td>
<td>29.4</td>
</tr>
<tr>
<td>3 Dependents Claimed</td>
<td>175</td>
<td>176</td>
<td>178</td>
<td>182</td>
<td>152</td>
<td>142</td>
<td>128</td>
<td>126</td>
<td>1,253</td>
<td>11.3</td>
</tr>
<tr>
<td>4 Dependents Claimed</td>
<td>74</td>
<td>75</td>
<td>63</td>
<td>62</td>
<td>57</td>
<td>53</td>
<td>47</td>
<td>43</td>
<td>475</td>
<td>4.3</td>
</tr>
<tr>
<td>5 Dependents Claimed</td>
<td>15</td>
<td>16</td>
<td>13</td>
<td>12</td>
<td>15</td>
<td>14</td>
<td>13</td>
<td>11</td>
<td>109</td>
<td>1.0</td>
</tr>
<tr>
<td>6 Dependents Claimed</td>
<td>7</td>
<td>4</td>
<td>4</td>
<td>6</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>31</td>
<td>0.3</td>
</tr>
<tr>
<td>7 Dependents Claimed</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>0.1</td>
</tr>
<tr>
<td>8 Dependents Claimed</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0.0</td>
</tr>
</tbody>
</table>

---

Research Design
\[ \ln \text{Contribution}_{it} = \alpha_0 + \beta_{0i} + \gamma_t + \]
\[ \beta_1 (\ln \text{Contribution}_{it-1}) + \]
\[ \beta_2 (\ln \text{Income}_{it-1}) + \]
\[ \beta_3 (\ln \text{Price}_{it-1}) + \beta_4 (\ln \text{Income}_{it}) + \]
\[ \beta_5 (\ln \text{Price}_{it}) + \]
\[ \beta_6 (\text{Marital Status}_{it}) + \beta_7 (\text{Age}_{it}) + \]
\[ \beta_8 (\text{Dependents}_{it}) + \]
\[ \beta_9 (\ln \text{Income}_{it+1}) + \]
\[ \beta_{10} (\ln \text{Price}_{it+1}) + \epsilon_{it} \]

(13)

The terms \( \alpha_0, \beta_{0i}, \) and \( \gamma_t \) represent the common intercept, donor-specific constants, and time-specific constants, respectively (see Appendix A for additional specification details).\(^1\) Because the dynamic two-way fixed-effects model of giving dominates its dynamic and static rivals on statistical, specification, and a priori theoretical grounds, it is used as an organizing framework in developing this study's research hypotheses (see Appendix A and Appendix B for details). The research hypotheses follow directly from the refutable propositions summarized in Table 1.1 and are presented in the same order in which their corresponding elasticities appear in equation (13).

\(^1\)One of the time-specific constants must be dropped in order to avoid perfect multicollinearity.
3.2.1 Hypotheses for testing individual elasticities.

According to the habit persistence argument, donors' learning about tax changes takes place with some delay. Consequently, factors underlying donors' past giving patterns continue to exert some residual influence on this year's giving. Thus, this year's gifts are positively related to last year's. This argument gives rise to the following competing hypotheses:

**H1A₀**: Donors learn about and respond to tax changes instantaneously. Thus, previous giving patterns exert no influence on this year's giving. This suggests that the coefficient on lagged giving is equal to zero.

**H1A₁**: Donors' learning about tax changes take place with a delay. Consequently, previous giving patterns exert some residual influence upon this year's giving. This suggests that the coefficient on lagged giving is greater than zero.

These competing hypotheses are evaluated with this one-sided test statistic:\[^62,63^]

[^62]: A technical distinction is worth noting. Within the habit-persistence framework introduced by Clotfelter (1980) and imposed, at least initially, on this study's dynamic models of giving (See Appendix A for a complete listing of the specifications of these dynamic models), each parameter estimate and combination will have both a short-run and long-run interpretation. If donors respond rapidly to taxation-induced changes in income and price, the distinction between the short- and long-run is trivial and should be abandoned. The following discussion provides the details underpinning this argument:

1. Begin with Clotfelter's habit-persistence model (equation 3), take the natural log of both sides, and simplify.
\[ c_t = \left[ \frac{c_t}{c_{t-1}} \right]^\Gamma \Rightarrow \text{ln}c_t - \text{ln}c_{t-1} = \Gamma(c_t^* - c_{t-1}) \Rightarrow \text{ln}c_t - \text{ln}c_{t-1} - \Gamma(\text{ln}c_t) = \Gamma(\text{ln}c_t^*) \]

\[ c_t^* \text{ and } c_{t-1}^* \text{ represent observed giving at times } t \text{ and } t-1. \quad c_t^* \text{ is the long-run desired level of giving and } \Gamma \text{ represent the coefficient of adjustment.} \]

\[ \Rightarrow \text{ln}c_t - (1 - \Gamma)\text{ln}c_{t-1} = \Gamma(\text{ln}c_t^*) \Rightarrow \text{ln}c_t = \Gamma(\text{ln}c_t^*) + (1 - \Gamma)\text{ln}c_{t-1} \]

2. When the dynamic two-way fixed-effects model is substituted for \( c_t^* \), the coefficient \( B_{10} \) is equivalent to \( (1 - \Gamma) \).

\[ \Rightarrow \text{ln}c_t = \Gamma(B_0 + B_1 \text{LAGINC} + B_2 \text{LAGPRC} + B_3 \text{LOGINC} + B_4 \text{LOGPRC} + B_5 \text{MARDUM} + B_6 \text{AGEDUM} + B_7 \text{NUMDEF} + B_8 \text{LEDINC} + B_9 \text{LEDPRC}) + B_{10} \text{LAGCON} + \text{error} \]

3. Given \( B_{10} = (1 - \Gamma) \), then \( \Gamma = 1 - B_{10} \).

\[ \Rightarrow \Gamma B_1 = \text{Short-Run Elasticity for Last Year's Income (LAGINC)}. \]

\[ \Rightarrow \Gamma B_1 / (1 - B_{10}) = B_1 = \text{Long-Run Elasticity for Last Year's Income}. \]

\[ \Rightarrow \text{As } (1 - B_{10}) \text{ approaches one (i.e., } (1 - \Gamma) \text{ approaches zero), the distinction between the short-run and long-run version of a parameter becomes trivial and, from a pragmatic point of view, is no longer worth making. Similar conclusions apply to all other elasticities appearing in the dynamic model.} \]

4. If the distinction between the short- and long-run is nontrivial, Clotfelter provides the approximate mean and variance for evaluating each long-run parameter estimate's statistical significance.

\[
E = \left[ \frac{\hat{B}_1}{1 - \hat{B}_{10}} \right] = \frac{\hat{B}_1}{1 - \hat{B}_{10}} + \frac{\text{COV}((\hat{B}_1, \hat{B}_{10}))(\text{VAR} \hat{B}_{10})^{1/2}}{(1 - \hat{B}_{10})^{2}} + \frac{\hat{B}_1 \text{ VAR} \hat{B}_{10}}{(1 - \hat{B}_{10})^{3}}
\]

\[
V = \left[ \frac{\hat{B}_1}{1 - \hat{B}_{10}} \right] = \frac{\text{VAR} \hat{B}_1}{1 - \hat{B}_{10}} + \frac{2\text{COV}((\hat{B}_1, \hat{B}_{10}))(\text{VAR} \hat{B}_{10})^{1/2}}{(1 - \hat{B}_{10})^{3}} + \frac{\hat{B}_1 \text{ VAR} \hat{B}_{10}}{(1 - \hat{B}_{10})^{4}}
\]

The dynamic two-way fixed-effects model has a coefficient on lagged giving of 0.1556 (0.0118). This implies that the coefficient of adjustment is equal to 0.8444. Thus, roughly 85 percent of donors' response to a change in disposable income and price takes place within one year of the change. This empirical evidence suggests that the donors examined in this study

Research Design 86
Increases in transient income are not 'rationally' consumed in the year of occurrence. Rather, consumption of each good, including giving, is smoothed. Consequently, this year's gifts are positively related to last year's income. These competing hypotheses apply:

**H1B0:** Changes in last year's disposable income have no impact on this year's giving. This suggests that last year's income elasticity is zero.

respond very rapidly to taxation-induced changes in disposable income and price. This raises an important question. Is there a noteworthy interpretational difference between the short-run and long-run versions of each of the elasticity parameters found in the dynamic two-way fixed-effects model? Using the long-run elasticity estimates as the point of reference, the following evidence addresses this question:

<table>
<thead>
<tr>
<th></th>
<th>LAGINC</th>
<th>LAGPRC</th>
<th>LOGINC</th>
<th>LOGPRC</th>
<th>LEDINC</th>
<th>LEDPRC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short-Run:</td>
<td>0.1571</td>
<td>0.3543</td>
<td>0.1873</td>
<td>-1.1808</td>
<td>0.0731</td>
<td>0.4280</td>
</tr>
<tr>
<td>Long-Run:</td>
<td>0.1861</td>
<td>0.4197</td>
<td>0.2219</td>
<td>-1.3984</td>
<td>0.0866</td>
<td>0.5070</td>
</tr>
<tr>
<td>Standard Errors</td>
<td>0.0299</td>
<td>0.1199</td>
<td>0.0476</td>
<td>0.1241</td>
<td>0.0438</td>
<td>0.1316</td>
</tr>
</tbody>
</table>

Conclusion:

Because the long-run elasticity estimates do not differ interpretationally from their short-run counterparts, Clotfelter's distinction between the long-run and short-run is dropped throughout the remainder of this study.

In the case of the dynamic two-way fixed-effects model, the introduction of lead and lag variables causes 1979 and 1986 to drop out of the model. Thus, for purposes of testing these and other hypotheses associated with the dynamic two-way fixed-effects model, N is equal to 8,292 (1,382 donors * 6 years per donor) observations.

Research Design
**H1B₁:** Donors do not rationally consume entire increases in disposable income in the year incurred. Instead, consumption is smoothed. Thus, donors experiencing increases in last year's disposable income give more in the current year, suggesting that last year's income elasticity is positive.

A test statistic similar to the one appearing in equation (14) is used to determine which of these competing hypotheses best accounts for the influence that last year's income exerts upon this year's giving.

Donors who faced a relatively higher price of giving last year postpone a portion of their intended gifts until 'this' year. Thus, this year's gifts are positively related to last year's price. The following competing hypotheses apply:

**H1C₀:** Last year's price does not influence this year's giving. This implies that last year's price elasticity is zero.

**H1C₁:** Donors who faced relatively higher prices last year shift a portion of last year's potential gifts into the current year. Thus, last year's price elasticity is positive.

A test statistic similar to the one generated by equation (14) is used to evaluate these competing hypotheses.

Because tax payments inhibit giving by reducing donors' disposable income, empirical estimates of this year's income elasticity should have a positive sign. This argument suggests the following competing hypotheses:

**H1D₀:** This year's giving does not respond to changes in this year's income-reducing tax payments. This suggests that this year's income
elasticity is zero.

**H1D**: Because this year's income-reducing tax payments inhibit this year's giving, this year's income elasticity is greater than zero.

Once again, the appropriate test statistic is generated by equation (14).\(^{64}\)

Because the charitable deduction stimulates giving by reducing its price, empirical estimates of this year's price elasticity should have a negative sign. Consequently, these hypotheses apply:

**H1E**: This year's giving does not respond to this year's price-reducing charitable deductions. This suggests that this year's price elasticity is zero.

**H1E**: This year's price-reducing charitable deductions increase giving, suggesting this year's price elasticity is negative.

Equation (14), generates the test statistic for evaluating these competing hypotheses.

Anticipated increases in next year's disposable income also result in 'smoothed' consumption, suggesting this year's contributions are positively related to next year's income. This refutable proposition motivates the following hypotheses:

**H1F**: Changes in next year's disposable income have no impact on this year's giving, suggesting next year's income elasticity is zero.

\(^{64}\)A one-sided test is used because contributions are assumed, a priori, to be normal rather than inferior goods. Thus, if the income elasticity is non-negative, then the price elasticity must be non-positive by consumer theory.
**H1P₁**: Donors who anticipate increases in next year's disposable income smooth a portion of their consumption into 'this' year. Thus, next year's income elasticity is greater than zero.

The appropriate test statistic comes from equation (14).

Donors respond to anticipated price increases by shifting a portion of next year's intended gifts into the 'this' year. Thus, this year's gifts are positively related to next year's price. Consequently, the following hypotheses are relevant:

**H1G₀**: Next year's price does not influence this year's giving, suggesting next year's price elasticity is zero.

**H1G₁**: Donors who face relatively higher prices next year shift a portion of next year's intended gifts into 'this' year, suggesting next year's price elasticity is greater than zero.

Evaluation of this final set of competing hypotheses relies upon a test statistic generated from equation (14).

### 3.2.2 Hypotheses for evaluating the deduction's efficiency.

Having established the framework for evaluating the significance and directionality of individual elasticity estimates, it is now appropriate to consider hypotheses involving linear combinations of individual elasticity estimates. Those combinations which facilitate assessment of the deduction's short-run and long-run efficiency are of particular interest in this section. When the efficiency analysis is restricted to the elasticity estimate associated
with this year's price, the following hypotheses are relevant:

$H_{1H_0}$: The short-run deduction-induced flow of resources into the nonprofit sector is less than the government's short-run deduction-induced revenue loss. This implies that this year's price elasticity is greater than negative one.

$H_{1H_1}$: The short-run deduction-induced flow of resources into the nonprofit sector either exactly offsets or exceeds the government's short-run deduction-induced revenue loss. This suggests that this year's price elasticity is less than or equal to negative one.

The short-run efficiency of the charitable deduction is evaluated with the following two-sided test statistic:

$$\hat{\beta}_5 + 1 \quad \text{ or } \quad t_{n-k-1} (15)$$

$$[\text{VARIANCE} (\hat{\beta}_5)]^{1/2}$$

When the analysis of efficiency is expanded to include last year's, this year's, and next year's price, the following hypotheses apply:

$H_{1I_0}$: The long-run deduction-induced flow of resources into the nonprofit sector is not equal to the government's long-run deduction-

---

65 The short-run and long-run terminology used in these two sets of hypotheses does not refer to the short-run versus long-run distinction noted by Clotfelter. The empirical evidence in this study suggests such a distinction is trivial. Instead, this terminology refers loosely to the distinction between donors' response to changes in this year's price and income and their cumulative response to changes in last year's, this year's, and next year's income and price. Donors' response to transitory changes in this year's income and/or price is referred to as their short-run response. Donors' cumulative response to transitory changes in last year's, this year's, and next year's income and/or price is referred to as their long-run response.

Research Design 91
induced revenue loss. This suggests that the sum of last year's, this year's, and next year's price elasticities is greater than negative one.

\( H_{1I_1} \): The long-run deduction-induced flow of resources into the nonprofit sector either exactly offsets or more than offsets the government's long-run deduction-induced revenue loss. This suggests that the sum of last year's, this year's, and next year's price elasticities is less than or equal to negative one.

These competing hypotheses are evaluated with an F test statistic from the following equation:

\[
F = \left[ \frac{N - K - 1}{R} \right] \left[ \frac{RSSE - USSE}{USSE} \right] - F(R, N - K - 1) \tag{16}
\]

RSSE is the sum of squared errors from a restricted model, USSE is the sum of squared errors from an unrestricted model, and \( R \) is the number of restrictions imposed upon the restricted model. To illustrate, the unrestricted sum of squared errors comes from the dynamic two-way fixed-effects model appearing in equation (13). The restricted sum of squared errors is generated from an auxiliary regression featuring the linear restriction implied by hypotheses \( H_{1I_0} \) and \( H_{1I_1} \):

\[
( \beta_3 + \beta_5 + \beta_{10} ) = -1 \tag{17}
\]

This restriction transforms equation (13) into the following auxiliary equation:
\[ \ln C_{it} + \ln P_{t-1} = \alpha_0 + \beta_{0i} + \gamma_t + \beta_1 \ln C_{it-1} + \beta_2 \ln Y_{it-1} + \beta_3 \ln Y_{it} + \beta_5 (\ln P_{it} - \ln P_{it-1}) + \beta_6 M_{st} + \beta_7 A_{ge_{it}} + \beta_8 D_{ep_{it}} + \beta_9 \ln Y_{it+1} + \beta_{10} (\ln P_{it+1} - \ln P_{it-1}) + \varepsilon_{it} \] (18)

\( \ln C_{it-1} \) and \( \ln C_{it} \) are last year's and this year's gifts. \( \ln Y_{it-1}, \ln Y_{it}, \) and \( \ln Y_{it+1} \) are last year's, this year's, and next year's disposable income. \( \ln P_{it-1}, \ln P_{it}, \) and \( \ln P_{it+1} \) are last year's, this year's, and next year's price of giving. \( M_{st} \) is marital status. \( D_{ep} \) is the number of dependents. The coefficients, \( \beta_5 \) and \( \beta_{10} \), represent this year's and next year's transformed prices, respectively. If the insight provided by the restricted model is statistically equivalent to the unrestricted model's, the linear restriction holds and the deduction is efficient in the long-run.

3.2.3 Hypotheses for evaluating neutrality.

When the analysis is expanded to include disposable income elasticities, one may assess whether giving is neutral to changes in marginal tax rates in both the short-run and long-run. Beginning with the short-run, the following competing hypotheses are relevant:

\( H1J_0: \) In the short-run, giving is not neutral to increases in marginal tax rates. This suggests that increases in tax rates either inhibit or stimulate this year's giving.

Research Design 93
H1J₁: In the short-run, giving is neutral to changes in marginal tax rates. That is, donors are just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments. This suggests that the sum of this year's income and price elasticities is equal to zero.

As applied to these hypotheses, an F test statistic generated from equation (16) facilitates evaluation of these competing hypotheses. To illustrate, suppose the unrestricted sum of squared errors comes from the dynamic two-way fixed-effects model appearing in equation (13). The restricted sum of squared errors is then generated from an auxiliary regression featuring the linear restriction implied by H1J₀ and H1J₁:

$$β₄ + β₅ = 0$$  \hspace{2cm} (19)

This restriction transforms the dynamic two-way fixed-effects model into the following auxiliary model:

$$\ln C_{it} = α₀ + β_{0i} + 8_t + β₁ \ln C_{it-1} + β₂ \ln Y_{it-1} +$$

$$β₃ \ln P_{it-1} + β₅ (\ln P_{it} - \ln Y_{it}) + β₆ MS_{it} +$$

$$β₇ Age_{it} + β₈ Dep_{it} + β₉ \ln Y_{it+1} + β₁₀ \ln P_{it+1} +$$

$$e_{it}$$ \hspace{2cm} (20)

$β₅$ is the elasticity for the transformed price of giving implied by equation (19). If the insight provided by the restricted model is statistically equivalent to the unrestricted model's, the linear restriction holds and giving is neutral to taxes in the short-run.

If this neutrality analysis is expanded to include last
year's, this year's, and next year's income and price elasticities, the following hypotheses apply:

**H1K₀**: In the long-run, giving is not neutral to increases in marginal tax rates. This suggests that increases in marginal tax rates either inhibit or stimulate this year's giving.

**H1K₁**: In the long-run, giving is neutral to changes in marginal tax rates. That is, in the long-run, donors are just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments. This suggests that the sum of last year's this year's, and next year's income and price elasticities is equal to zero.

This long-run version of neutrality is evaluated with an F test statistic obtained from equation (16). To illustrate, the unrestricted sum of squared errors comes from the dynamic two-way fixed-effects model appearing in equation (13). The restricted sum of squared errors is obtained from an auxiliary regression featuring the linear restriction implied by hypotheses **H1K₀** and **H1K₁**:

\[( β_3 + β_5 + β_{10} ) + ( β_2 + β_4 + β_9 ) = 0 \]  
\[(21)\]

This restriction transforms equation (13) into the following equation:

\[\ln C_{it} = α_0 + β_{0i} + \gamma_t + β_1 \ln C_{it-1} + \]
\[β_2 (\ln Y_{it-1} - \ln P_{it-1}) + β_4 (\ln Y_{it} - \ln P_{it-1}) + \]
\[β_5 (\ln P_{it} - \ln P_{it-1}) + β_6 MS_{it} + β_7 Age_{it} + \]
\[β_8 Dep_{it} + β_9 (\ln Y_{it+1} - \ln P_{it-1}) + \]
\[β_{10} (\ln P_{it+1} - \ln P_{it-1}) + e_{it} \]  
\[(22)\]
If the insight provided by the restricted model is statistically equivalent to the unrestricted model's, the linear restriction holds and giving is neutral to taxes in the long-run. Tests of individual elasticity estimates and the linear combinations required to evaluate efficiency and neutrality will facilitate resolution of this study's research questions.
This chapter presents the empirical findings generated while carrying out the research design. The dynamic two-way fixed-effects model dominates its dynamic and static rivals on statistical, specification, a priori theoretical grounds.\textsuperscript{66} Consequently, this year's giving is best understood after:

1. Controlling for donor- and time-specific effects.
2. Including conventional measures for this year's disposable income and price.
3. Taking into account the incremental information contained in last year's income and price, next year's income and price, and donors' habit persistence tendencies.

With the exception of next year's marginally significant income elasticity ($P = 0.0663$), each of the dynamic model's elasticity estimates are highly significant and have the anticipated signs.

Because individual coefficients are at least marginally significant, it is appropriate to combine them to accommodate the linear restrictions needed for assessing efficiency and

\textsuperscript{66} Appendix A contains the details which establish this model's statistical dominance. Appendix B contains the details which establish this model's specification dominance. The theoretical framework presented in Chapter one, together with the empirical results reported in this Chapter, establish the a priori theoretical dominance of the dynamic way-way fixed-effects model.
neutrality. When the scope of analysis is restricted to efficiency, this year's price elasticity of -1.1808 (with a standard error of 0.1158) indicates that the charitable deduction is efficient in the short-run. When efficiency is expanded to include last year's, this year's, and next year's price elasticities, the sum of these elasticities, -0.3985 (0.1691), is greater than negative one. This finding implies that the deduction is treasury inefficient in the long-run.\(^7\)

When the scope of analysis is expanded to accommodate neutrality, the sum of this year's income and price elasticities is -0.9935 (0.1318). This means that in the short-run, donors are much more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Thus, increases in marginal tax rates stimulate donors' short-run giving. When neutrality is expanded to include last year's, this year's, and next year's income and price elasticities, the sum of these elasticities is 0.0190

\(^{67}\) The short-run and long-run terminology used in this discussion does not refer to the short-run versus long-run distinction noted by Clotfelter (1980). The empirical evidence in this study suggests such a distinction is trivial. Instead, this terminology refers loosely to the distinction between donors' response to changes in this year's price and income and their cumulative response to changes in last year's, this year's, and next year's income and/or price. Donors' response to transitory changes in this year's income and/or price is referred to as their short-run response. Donors' cumulative response to transitory changes in last year's, this year's, and next year's income and/or price is referred to as their long-run response.

Empirical Findings 98
(0.1964). This implies that in the long-run, donors are just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments. In other words, within a three-year window, donors do not change their total contributions, they simply manipulate the timing of these contributions in such a way as to neutralize changes in marginal tax rates.

Taken together, the short-run efficiency and neutrality results reported above indicate that the deduction is an efficient means of stimulating giving. This finding provides a harmonizing link to the traditional literature. When the dynamic model is restricted to a static portrayal of giving, it yields the same policy and managerial implications as its traditional static counterparts. This means that traditional estimates are probably capturing donors' short-run response to changes in price and income. In contrast, long-run results suggest that the deduction is an inefficient means of neutralizing donors' response to changes in marginal tax rates. These short-run and long-run findings provide an interesting contrast to those reported in prior panel studies.

Although the dynamic two-way fixed-effects model dominates rival models on statistical, specification, and a priori theoretical grounds, it still suffers from violations of underlying statistical assumptions. This implies that the

**Empirical Findings**
dynamic model's elasticity estimates may be biased and thus unable to provide reliable insights into theoretical relationships. However, the large sample utilized in this study may cause pragmatically irrelevant statistical violations to be statistical significant. At worst, the violations of this model are no more severe than those associated with the econometric models employed in prior research (see Appendix A for a full discussion of this issue). For this reason, these results are provided on a "subject to" basis for interested readers.

4.1 The Dynamic Two-Way Fixed-Effects Model of Giving.\(^{68,69}\)

Table 4.1 displays the parameter estimates obtained when estimating the dynamic two-way fixed-effects model of giving.

---

\(^{68}\) Parameter estimates are generated using LIMDEP's (Limited Dependent Variables) panel-data estimation algorithms [Green (1990a)]. This statistical package was chosen for this study because, unlike the other contemporary statistical packages, it has ready-to-use algorithms for computing panel-data parameters.

\(^{69}\) There has been some discussion regarding the relevant range of the elasticity estimates generated by this and similar studies. The elasticity estimates reported in this study are generated from a sample of middle-class itemizing taxpayers from the United States. Thus, the relevant range is limited to the response patterns of this particular group of donors. By implication, these elasticity estimates probably do not accurately reflect the response patterns of wealthy itemizing donors in the United States or donors in countries having substantially different tax regimes.

Empirical Findings
### Table 4.1 The Dynamic Two-Way Fixed-Effects Model: Parameter Estimates and Correlation Coefficients

#### The Estimated Dynamic Two-Way Fixed-Effects Model of Charitable Giving

\[
\begin{align*}
\text{LN CONTRIBUTIONS}_{it} &= 0.3747 + 0.1556 (\text{LN CONTRIBUTIONS}_{it-1}) + 0.1571 (\text{LN INCOME}_{it-1}) + \\
&\quad (0.5931) (0.0118) + (0.0418)
\end{align*}
\]

\[
0.3543 (\text{LN PRICE}_{it-1}) + 0.1873 (\text{LN INCOME}_{it}) - 1.808 (\text{LN PRICE}_{it}) + \\
(0.1107) (0.0436) + (0.1158)
\]

\[
0.5138 (\text{MARITAL STATUS}_{it}) + 0.0168 (\text{AGE}_{it}) - 0.0076 (\text{DEPENDENTS}_{it}) + \\
(0.0586) (0.0698) + (0.0183)
\]

\[
0.0731 (\text{LN INCOME}_{it+1}) + 0.4280 (\text{LN PRICE}_{it+1}) + \\
(0.0403) (0.1214)
\]

*Amounts in brackets are standard errors.

#### Pearson Correlation Coefficients (Amounts in Brackets Are P-Values)

<table>
<thead>
<tr>
<th></th>
<th>C_0</th>
<th>C_1</th>
<th>Y_1</th>
<th>P_1</th>
<th>Y_0</th>
<th>P_0</th>
<th>MS_0</th>
<th>AGE_0</th>
<th>DEP_0</th>
<th>Y_{+1}</th>
<th>P_{+1}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.000</td>
<td>0.175</td>
<td>0.118</td>
<td>-0.069</td>
<td>0.192</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>C_{-1}</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Y_{-1}</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Y_{+1}</td>
<td>1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

#### Key:
- \( C_0 = \ln(\text{CONTRIBUTION}_{it}) \)
- \( C_{-1} = \ln(\text{CONTRIBUTION}_{it-1}) \)
- \( Y_1 = \ln(\text{INCOME}_{it-1}) \)
- \( P_1 = \ln(\text{PRICE}_{it-1}) \)
- \( P_0 = \ln(\text{PRICE}_{it}) \)
- \( Y_0 = \ln(\text{INCOME}_{it}) \)
- \( MS_0 = \text{MARITAL STATUS}_{it} \)
- \( AGE_0 = \text{AGE}_{it} \)
- \( DEP_0 = \text{DEPENDENTS}_{it} \)
- \( Y_{+1} = \ln(\text{INCOME}_{it+1}) \)
- \( P_{+1} = \ln(\text{PRICE}_{it+1}) \)

Empirical Findings 101
Please notice that donor- and time-specific constants are not reported. This reporting strategy is a matter of necessity and is not intended to lessen the importance of donor- and time-specific effects.\textsuperscript{70} In addition, Table 4.1 contains the Pearson correlation coefficients for the variables appearing in the dynamic two-way fixed-effects model of giving. Although the correlation coefficients for last year's price and income (-0.569), this year's price and income (-0.572), and next year's price and income (-0.618) have the largest absolute values, they are still considerably smaller than the rule-of-thumb values (0.900 or higher) which indicate that multicollinearity is a problem. Thus, as claimed in footnote 38 (page 64), there is enough independent variation in the price variable to provide meaningful price elasticities.

To assist the reader in cross-referencing, Table 4.2 indicates which refutable proposition is tested by a particular set of competing hypotheses. The reference to each refutable proposition provides a link back to Table 1.1, Summary of Refutable Propositions Motivated by a Dynamic Version of Consumer Theory. Table 1.1 then in turn provides

\textsuperscript{70} Indeed, Appendix B clearly indicates that it is very important to control for donor- and time-specific effects when explaining this year's giving. Reporting each of these constants is not feasible because a total of 1,387 parameter estimates would have to be reported in order to reveal each donor- and time-specific constant.

Empirical Findings 102
### Panel A
#### Research Hypotheses for Individual Elasticity Estimates

<table>
<thead>
<tr>
<th>Competing Hypotheses</th>
<th>Refutable Proposition</th>
<th>Elasticity Estimate</th>
<th>Standard Error</th>
<th>T-Ratio</th>
<th>Probability</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1A0 vs H1A1</td>
<td>c1 &gt; 0</td>
<td>0.1556</td>
<td>0.0118</td>
<td>13.23</td>
<td>0.0000</td>
<td>c1 &gt; 0</td>
</tr>
<tr>
<td>H1D0 vs H1D1</td>
<td>y0 &gt; 0</td>
<td>0.1571</td>
<td>0.0418</td>
<td>3.76</td>
<td>0.0003</td>
<td>y0 &gt; 0</td>
</tr>
<tr>
<td>H1C0 vs H1C1</td>
<td>p1 &gt; 0</td>
<td>0.3543</td>
<td>0.1107</td>
<td>3.20</td>
<td>0.0016</td>
<td>p1 &gt; 0</td>
</tr>
<tr>
<td>H1E0 vs H1E1</td>
<td>y1 &gt; 0</td>
<td>0.1873</td>
<td>0.0436</td>
<td>4.29</td>
<td>0.0000</td>
<td>y1 &gt; 0</td>
</tr>
<tr>
<td>H1F0 vs H1F1</td>
<td>p1 &lt; 0</td>
<td>-1.1808</td>
<td>0.1158</td>
<td>-10.19</td>
<td>0.0000</td>
<td>p1 &lt; 0</td>
</tr>
<tr>
<td>H1G0 vs H1G1</td>
<td>y1 &gt; 0</td>
<td>0.0731</td>
<td>0.0403</td>
<td>1.81</td>
<td>0.0653</td>
<td>y1 &gt; 0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Panel B
#### Research Hypotheses for Evaluating the Deduction's Treasury Efficiency

<table>
<thead>
<tr>
<th>Competing Hypotheses</th>
<th>Refutable Proposition</th>
<th>Elasticity Estimate</th>
<th>Standard Error</th>
<th>T-Ratio</th>
<th>p Value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1H0 vs H1H1</td>
<td>P0 = -1</td>
<td>-1.1808</td>
<td>0.1158</td>
<td>-1.56</td>
<td>&lt; 0.05</td>
<td>Efficient in Short-Run</td>
</tr>
<tr>
<td>H1I0 vs H1I1</td>
<td>P-1 + P0 + P+1 = -1</td>
<td>-0.3985</td>
<td>0.1562</td>
<td>3.65</td>
<td>&lt; 0.005</td>
<td>Inefficient in Long-Run</td>
</tr>
</tbody>
</table>

**p(-1.1808 + 1.00 / 0.1158) = -1.56; p(-0.3985 + 1) / 0.1562 = 3.65**

### Panel C
#### Research Hypotheses for Evaluating Neutrality (How Changes in Marginal Tax Rates Impact Giving)

<table>
<thead>
<tr>
<th>Competing Hypotheses</th>
<th>Refutable Proposition</th>
<th>Elasticities</th>
<th>Std. Err.</th>
<th>T Ratio</th>
<th>p Value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1J0 vs H1J</td>
<td>y0 + P0 = 0</td>
<td>-0.9935</td>
<td>0.1318</td>
<td>-7.54</td>
<td>&lt; 0.01</td>
<td>Stimulates in Short-Run Neutral in Long-Run</td>
</tr>
<tr>
<td>H1K0 vs H1K</td>
<td>(P-1 + P0 + P+1) + (y0 + y0 + y1) = 0</td>
<td>0.0190</td>
<td>0.1964</td>
<td>0.10</td>
<td>&gt; 0.10</td>
<td></td>
</tr>
</tbody>
</table>

**Key:** c1 = ln contributionsit−1; y1 = ln incomeit−1; P−1 = ln priceit−1; y0 = incomeit; P0 = ln priceit; y1 = ln incomeit+1; and P1+1 = ln priceit+1

***The test statistics for these competing hypotheses were computed by hand. Consequently, I had to rely on standard probability tables. For this reason, a precise p value cannot be provided for the reader. However, the approximate p values should be sufficient to allow the reader to discriminate between competing hypotheses.***

Empirical Findings 103
a link to the theoretical arguments that motivate each refutable proposition. Similarly, the reference made to each set of competing hypotheses provides a link back to the relevant motivating paragraphs in Chapter 3. For each refutable proposition, Table 4.2 also discloses the accompanying elasticity estimate, standard error, T-Ratio, probability or P value, and conclusion.

4.1.1 Individual elasticity estimates.

Using the dynamic two-way fixed-effects model featured in Table 4.1 as the reference point, the discussion now focuses upon the test statistics and implications of each of the individual parameter estimates appearing in this model. The individual elasticity estimates are now discussed in precisely the same order in which they appear in Table 4.2 (Panel A) and the dynamic model featured in Table 4.1.

The highly significant positively signed elasticity estimate associated with last year's gifts (C_{-1} and ln Contributions_{it-1}), 0.1556 (standard error 0.0118), is in harmony with prior expectations. This evidence suggests that donors' learning about tax changes take place with a very small delay. Thus, last year's transitory giving patterns

---

71The term transitory is used because individual-specific effects control for permanent giving patterns that influence this year's giving.
do not exert much influence on this year's giving. In particular, a 10 percent increase in last year's giving results in roughly a 2 percent increase in current giving, ceteris paribus. Conversely, a 10 percent decrease in last year's giving results in a 2 percent decrease in this year's giving.

When interpreted in Clotfelter's habit-persistence framework, the complement of this elasticity yields a coefficient of adjustment equal to 0.8444 \((1 - 0.1556)\). This means that roughly 85 percent of the percentage change in long-run giving is realized within one year of a policy-induced change in marginal tax rates. Ninety-eight percent \((1 - (0.1556)^2)\) is realized within two years of the change. Because donors' giving responds very rapidly to a policy-induced change in disposable income and price, Clotfelter's distinction between donors' short-run and long-run response is pragmatically trivial.

To illustrate, consider the highly significant positively signed elasticity estimate associated with last year's disposable income \((Y_{-1}\) and \(\ln\text{Income}_{it-1}\)) of 0.1571 (0.0418). Taken at face value, this evidence indicates that a portion of the potential consumption associated with increases in last year's transitory income is smoothed into the current year. Consequently, increases in last year's disposable income
increase this year's giving. For example, if last year's disposable income increased by 10 percent, donors' short-run response is to increase this year's giving by about 2 percent, ceteris paribus. Conversely, when donors experience a 10 percent decrease in last year's disposable income, their short-run response is to decrease this year's giving by about 2 percent.

The long-run income elasticity for last year's giving is 0.1860 (0.1571 / 0.8444). Thus, donors' long-run response to changes in last year's income is interpretationally identical to their short-run response. Because similar results are obtained for each of the remaining elasticity estimates, Clotfelter's distinction between donors' short- and long-run response to policy-induced changes in marginal tax rates is abandoned and individual parameter estimates are taken at face value.\textsuperscript{72,73}

\textsuperscript{72} See footnote 62 (page 85) for additional details.

\textsuperscript{73} The reader may also be interested in the estimation results of this non-habit persistence model (i.e., a model without lagged giving):

\[
\ln \text{Contribution}_{it} = 0.4708 + 0.2147 (\ln \text{Income}_{it-1}) + \\
(0.6004) (0.0421) \\
0.2293 (\ln \text{Price}_{it-1}) + 0.2021 (\ln \text{Income}_{it}) - \\
(0.1116) (0.0442) \\
1.1142 (\ln \text{Price}_{it}) + 0.5484 (\text{Marital Status}_{it}) + \\
(0.1172) (0.0593) \\
0.0231 (\text{Age}_{it}) - 0.0035 (\text{Dependent}_{it}) + \\
(0.0707) (0.0182) \\
0.0822 (\ln \text{Income}_{it+1}) + 0.5276 (\ln \text{Price}_{it+1}) + \\
(0.0408) (0.1227)
\]

\textbf{Empirical Findings}
In harmony with prior expectations last year's highly significant positively signed price elasticity of 0.3543 (0.1107) implies that donors who faced a relatively higher

Adjusted R-Squared: 0.7816

These results can be contrasted to those of the dynamic two-way fixed-effects model:

\[
\ln \text{Contribution}_{it} = 0.3747 + 0.1556 (\ln \text{Contribution}_{it-1}) + \\
(0.5931) (0.0118) \\
0.1571 (\ln \text{Income}_{it-1}) + 0.3543 (\ln \text{Price}_{it-1}) + \\
(0.0418) (0.1107) \\
0.1873 (\ln \text{Income}_{it}) - 1.1808 (\ln \text{Price}_{it}) + \\
(0.0436) (0.1158) \\
0.5138 (\text{Marital Status}_{it}) + 0.0148 (\text{Age}_{it}) - \\
(0.0586) (0.0698) \\
0.0073 (\text{Dependents}_{it}) + 0.0731 (\ln \text{Income}_{it+1}) + \\
(0.0184) (0.0403) \\
0.4280 (\ln \text{Price}_{it+1}) \\
(0.1214)
\]

Adjusted R-Squared: 0.7870

Using the elasticity estimates from the dynamic two-way fixed-effects model as the point of reference, the following evidence addresses whether the elasticity estimates of the non-habit persistence model differ interpretationally from those of the dynamic two-way fixed-effects model:

\[
\begin{array}{cccccc}
Y_{-1} & P_{-1} & Y_0 & P_0 & Y_{+1} & P_{+1} \\
\end{array}
\]

Habit Persistence: 0.1571 0.3543 0.1873 -1.1808 0.0731 0.4280 
(0.0418) (0.1107) (0.0436) (0.1158) (0.0403) (0.1214)

No-Habit Persistence: 0.2147 0.2293 0.2021 -1.1142 0.0822 0.5276

Where \( Y_{-1} \) is last year's income (\( \ln \text{Income}_{it-1} \)), \( P_{-1} \) is last year's price (\( \ln \text{Price}_{it-1} \)), \( Y_0 \) is this year's income (\( \ln \text{Income}_{it} \)), \( P_0 \) is this year's price (\( \ln \text{Price}_{it} \)), \( Y_{+1} \) is next year's income (\( \ln \text{Income}_{it+1} \)), and \( P_{+1} \) is next year's price (\( \ln \text{Price}_{it+1} \)).

This empirical evidence suggests that the non-habit persistence elasticity estimates have essentially the same pragmatic implications as their habit persistence counterparts.

**Empirical Findings**
price of giving last year shift a portion of their intended gifts into 'this' year. Thus, last year's price is positively related to this year's giving. Accordingly, a 10 percent increase in last year's price increases current giving by about 4 percent, ceteris paribus. Conversely, a 4 percent reduction in this year's gifts would have taken place if donors had experienced a 10 reduction in last year's price of giving.

The elasticity estimate associated with this year's disposable income \( (Y_0 \text{ and } \ln \text{Income}_{it}) \), 0.1873 (0.0436), is highly significant and has the anticipated positive sign. The magnitude of this estimate is much smaller than traditional and prior panel estimates. However, traditional estimates do not include donor-specific intercepts and thus confound the effects of permanent and transitory changes in income in one coefficient. In contrast here, permanent income effects are confounded in the donor-specific intercepts, so that the coefficient on income represents the pure impact of transitory income change. Further, estimates from prior static panel-data models may be impounding a portion of the explanatory prowess which should have been attributed to last year's giving, income, and price and next year's income and price.

This year's disposable income elasticity suggests that
when donors smooth the potential consumption associated with transitory increases in this year's disposable income, a portion of this potential consumption is realized 'this' year. Thus, increases in this year's transitory income increase this year's giving. In particular, a 10 percent increase in this year's disposable income brings about a 2 percent increase in this year's giving, ceteris paribus. Conversely, a 10 percent decrease in this year's disposable income reduces this year's gifts by 2 percent.

This year's price elasticity of -1.1808 (0.1158) is highly significant and has the anticipated negative sign. This new empirical evidence indicates that donors respond to increases in this year's price by shifting a portion of their intended gifts into subsequent years. Consequently, this year's giving is negatively related to this year's price. This means that a 10 percent increase in this year's price brings about a 12 percent reduction in this year's giving, ceteris paribus. Conversely, a 10 decrease in this year's price causes a 12 percent increase in this year's giving. Besides providing an interesting contrast to nearly all of the price elasticities reported in the panel-data literature, this new estimate is in harmony with traditional estimates.

Although appropriately signed, the elasticity estimate associated with next year's income elasticity of 0.0731

Empirical Findings
(0.0403) is only marginally significant \((P = 0.0663)\). However, an errors-in-measurement argument suggests that the lead variable on disposable income is an imperfect surrogate for next year's price. Consequently, the elasticity estimate associated with next year's disposable income is biased, presumably towards zero.\(^74\) Because the elasticity estimate for next year's disposable income is at least marginally significant, next year's income offers sufficient insight into this year's giving to warrant further discussion.

Next year's income elasticity estimate indicates that donors smooth a portion of the anticipated consumption associated with transitory increases in next year's disposable income into 'this' year. Thus, increases in next year's disposable income increase this year's giving. In particular, an anticipated increase of 10 percent in next year's disposable income increases current giving by about 1 percent, ceteris paribus. Conversely, an anticipated decrease of 10 percent in next year's disposable income reduces this year's giving by about 1 percent.

The highly significant positively signed elasticity estimate associated with next year's price, 0.4280 (0.1214), implies that donors who face rising prices next year shift a

\(^{74}\) See footnote 48 (page 72) for additional support of this argument.
portion of next year's potential gifts into 'this' year. Thus, increases in next year's price increase this year's gifts. This means that a 10 percent increase in next year's price increases this year's giving by a little more than 4 percent. Conversely, a 10 percent decrease in next year's price will reduce this year's giving by about 4 percent.

4.2 Combining Individual Elasticity Estimates.\textsuperscript{75}

Having examined the test statistics and implications associated with each of the individual elasticity estimates appearing in the dynamic two-way fixed-effects model, the focus of discussion now shifts to the test statistics and implications associated with the linear combinations used to examine the deduction's efficiency and neutrality. Because individual elasticity estimates are at least marginally significant, combining them to form the linear restrictions needed for evaluating efficiency and neutrality is a meaningful way to proceed.

\textsuperscript{75}As noted in Table 4.2, the test statistics used in discriminating between the competing hypotheses associated with the linear combinations of parameter estimates used to evaluate the deduction's efficiency and whether donors' are neutral towards changes in marginal tax rates, were computed by hand. Consequently, I had to rely on standard probability tables. For this reason, precise P values cannot be provided for the reader. However, the approximate P values should be sufficient to allow the reader to discriminate between competing hypotheses.
4.2.1 The case of efficiency.

When the efficiency analysis is restricted to this year's price elasticity estimate, the relevant $t_{6895}$ (Degrees of Freedom) test statistic from Panel B of Table 4.2, $-1.5617 ((-1.1808 + 1) / 0.1158)$, suggests that this elasticity is less than or equal to $-1.00$ at $P$ greater than 0.05 but less than 0.10. This implies that government subsidization of itemizers' giving is efficient in the short-run, ceteris paribus. That is, in the short-run, the deduction-induced flow of resources into the nonprofit sector offsets the government's deduction-induced revenue loss.

When the efficiency analysis is expanded to include last year's, this year's, and next year's price elasticity estimates, the sum of these estimates is $-0.3985 (0.1691)$. The applicable $F_{1,6895}$ test statistic, 12.6325, is generated by equation (16). This empirical evidence suggests that an auxiliary model whose price elasticities are constrained to sum to negative one differs significantly from the dynamic two-way fixed-effects model whose price elasticities are not subject to such a constraint. Thus, with a $P$ value $< 0.01,$

$^{76}$Alternatively, one could generate the following one-sided $t_{6895}$ test statistic: $(-0.3985 + 1) / 0.1562 = 3.8508$. With a $P$ value $< 0.005$, this empirical evidence also suggests that the sum of these price elasticities is not equal to negative one (i.e., the positive sign of the test statistic suggests that the sum is greater than negative one).
the sum of the dynamic model's price elasticities is greater than negative one. This finding implies that the charitable deduction is inefficient in the long-run. That is, in the long-run, the deduction-induced flow of resources into the nonprofit sectors is less than the government's deduction-induced revenue loss.

4.2.2 The case of neutrality.

By including the elasticity estimates associated with last year's, this year's, and next year's disposable income, the scope of analysis can be expanded to accommodate an evaluation of neutrality. As noted in Panel C of Table 4.2, the sum of this year's income and price elasticities, \(-0.9935 (0.1318)\), is useful in assessing donors' short-run response to policy-induced changes in marginal tax rates. Drawing upon equation (16), the applicable \(F_{1,6895}\) test statistic, 47.3218, indicates that an auxiliary model whose income and price elasticities are constrained to equal zero differs significantly from the dynamic two-way fixed-effects model whose income and price elasticities are subjected to no such constraint.\(^77\) With a P value < 0.01, this empirical evidence

\(^77\)The following two-sided \(t_{6895}\) test statistic: \((-0.9935 + 0) / 0.1318\) = \(-7.5379\) (P < 0.01) also suggests that the sum of this year's income and price elasticities is not equal to zero (i.e., the negative sign of the test statistic suggests that the sum is less than zero).
implies that in the short-run donors are much more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Thus, in the short-run, increases in marginal tax rates stimulate giving, ceteris paribus.

When the neutrality analysis is expanded to include last year's, this year's, and next year's price and income elasticities, the sum of these elasticities, 0.0190 (0.1964), is useful in assessing donors' long-run response to taxes. Drawing once again upon equation (16), the applicable $F_{1,6895}$ test statistic, 0.0083, indicates that an auxiliary model whose income and price elasticities are constrained to equal zero is statistically identical to the dynamic two-way fixed-effects model whose income and price elasticities are subjected to no such constraint.\footnote{Alternatively, one could generate the following $t_{6895}$ test statistic: \( (0.0190 + 0) / 0.1964 \) = 0.0967. Unless one is willing to accept P values considerably in excess of 0.10, this empirical evidence also suggests that the sum of these elasticities is equal to zero.} Unless one is willing to accept P values considerably in excess of 5 percent, this empirical evidence implies that in the long-run donors are just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments. Thus, in the long-run, giving is neutral to changes in marginal tax rates, ceteris paribus. In other words, within a three-year window,
donors do not change their total contributions, they simply manipulate the timing of these contributions in such a way as to neutralize changes in marginal tax rates.

4.3 Other Considerations.

Of the three demographic variables introduced to proxy for differences in donors' utility functions, only marital status, 0.5138 (0.0586), provides statistically significant insight into changes in this year's giving (please refer to Table 4.1). The positive sign accompanying this parameter estimate is in harmony with traditional findings and suggests that marriage increases donors' giving. Although appropriately signed, the coefficient associated with the age variable, 0.0148 (0.0698), fails to provide statistically significant evidence for concluding generosity increases with a change to 'old age'. The statistical insignificance of the dependents coefficient, -0.0076 (0.0183), greatly mitigates the relevance of its inappropriate sign. Cross-sectional studies often find each of these demographic variables to be significant, but here, much of the impact of marriage, age, and dependents is confounded with the donor-specific effects because few donors shifted age, marital status, or the number of dependents over the time period examined.
4.4 Summary.

When taken together, the short-run efficiency and neutrality results reported above indicate that the deduction is an efficient means of stimulating giving. This finding provides a harmonizing link to the traditional literature. When the dynamic model is restricted to a static portrayal of giving, it yields the same policy and managerial implications as its traditional static counterparts. This means that traditional estimates are probably capturing donors' short-run response to changes in price and income. In contrast, long-run results suggest that the deduction is an inefficient means of neutralizing donors' response to changes in marginal tax rates. Besides providing a harmonizing link to the traditional literature, these findings provide an interesting contrast to those reported in prior panel studies and underscore the importance of reexamining model specification and estimation.
5.0 CONCLUDING REMARKS

This concluding chapter contains three sections. The first section provides a summary of this study. This summary touches on the motivation for conducting this research, the theoretical and econometric frameworks chosen, and the empirical findings and accompanying implications. The second section addresses this study's limitations. The final section considers the most likely extensions of this study.

5.1 A Summary of the Study.

Because the nonprofit sector plays an important role in the U.S. economy, the economic well-being of the organizations making up this sector is of interest to policy makers and nonprofit managers. The economic well-being of these organizations, and thus their ability to provide desired levels of goods and services, depends largely upon the availability of funding. Charitable contributions provide an important source of funding for many nonprofit organizations. In order to nurture this source of funding, policy makers and nonprofit managers must deepen their understanding of donors' giving behavior.
Consumer theory provides a useful framework for examining how the government's taxation decisions influence donors' giving behavior. Within this framework, taxes influence giving in two ways. Price-reducing charitable deductions stimulate giving and income-reducing tax payments inhibit giving. The opposing nature of these effects betrays taxation's analytically ambiguous impact on donors' giving. By implication, policy researchers must appeal to the empirical realm for additional insight into taxation's behavioral implications.

With traditional empirical income and price elasticities clustering around 0.70 and -1.30, donors are more responsive to price-reducing charitable deductions than they are to income-reducing tax payments, ceteris paribus. This implies that taxes stimulate giving. Because the representative price elasticity is less than negative one, the charitable deduction is also efficient.

This traditional understanding was recently challenged by studies employing observations on the same individuals at successive points in time (panel data). By focusing on how the charitable-giving behavior of a given set of donors changes in response to changes in their individual circumstances, panel-data elasticities more closely approximate 'true' causality. Because they are more
persuasive, panel-data elasticities pose a serious challenge to the traditional understanding.

Although most price elasticities generated from earlier panel-data studies suggest that the charitable deduction is inefficient, compelling evidence also exists for concluding that the charitable deduction is efficient. When examined jointly, income and price elasticities imply that donors are either more responsive to income-reducing tax payments than they are to price-reducing charitable deductions, just as responsive to income-reducing tax payments and price-reducing charitable deductions, or more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Thus, giving is either stimulated by, inhibited by, or neutral to taxes.

Because prior expectations lead one to believe they are more persuasive, the inability of earlier panel-data elasticity estimates to form a consensus is quite disconcerting. The resulting uncertainty reduces nonprofit managers' and policy makers' understanding of the charitable-giving phenomena, thus impeding effective policy decisions and governance of nonprofit organizations.

The conflicting nature of these results probably stems from prior researchers use of model specifications that are incapable of providing an adequate summary of the unique

Concluding Remarks
information contained in alternative data sets. Regardless of the data set examined, nearly all earlier empirical models portray giving as a static activity. That is, this year's gifts are modeled as though they are made independent of donors' habit persistence tendencies and last year's and next year's prices and disposable incomes. This restrictive assumption is easily relaxed when consumer theory's habit persistence and life cycle arguments are considered. These arguments reveal that in addition to this year's price and income elasticities, consumer theory motivates 'new' elasticities which account for the ways in which giving is influenced by donors' habit persistence, last year's price and income, and next year's price and income. This implies that the restricted or static model of giving is a special case of a more general or dynamic model of giving that portrays this year's giving as a 'dynamic' activity. This portrayal is especially appealing when observable realizations of the data-generating mechanism reflect a time dimension and/or emanate from the same donors.

Using a methodology which combines the best aspects of earlier panel studies, a richer utilization of consumer theory, and formal tests of statistical and specification adequacy, this study seeks to resolve the empirical realm's interpretational dilemma by addressing the following research

Concluding Remarks

120
questions. Does statistical analysis verify what logic suggests: that dynamic models dominate static models on statistical, specification, and a priori theoretical grounds? Is the static model a suitable approximation when data do not allow estimation of the dynamic model? In a full-fledged dynamic model, is the traditional understanding reestablished (taxation encourages giving and charitable deductions are treasury efficient) or additional support found for prior panel estimates? Does the data obey statistical assumption necessary to draw robust inference from these results?

Given conventional operational considerations and an econometric framework reflecting a synthesis of Hsiao's (1986) panel-data analysis monograph and Spanos's (1986) econometric modeling methodology, two sets of estimable models, one reflecting static models and the other dynamic models of giving, are set in array, one against the other. The set of static models contains cross-sectional, one-way fixed- and random-effects, and two-way fixed- and random-effects models. With the exception of the cross-sectional model, the set of dynamic models contains the dynamic counterparts of each of the models appearing in the set of static models.

The resulting analyses indicate that the dynamic two-way fixed-effects model dominates its dynamic and static rivals on statistical (see Appendix A), specification (see Appendix
B), and a priori theoretical grounds (see Chapters 1 and 4). This finding implies that this year's giving is best understood after controlling for donor- and time-specific effects and taking into account donors' habit persistence tendencies, last year's disposable income and price, and next year's disposable income and price. With the exception of next year's marginally significant income elasticity (P = 0.0663), each of the dynamic model's elasticity estimates are highly significant and have the anticipated signs.

Because individual coefficients are at least marginally significant, it is appropriate to combine them to accommodate the linear restrictions needed for assessing efficiency and neutrality. When the scope of analysis is restricted to efficiency, this year's price elasticity of -1.1808 (with a standard error of 0.1158) indicates that the deduction is efficient in the short-run. When efficiency is expanded to include last year's, this year's, and next year's price elasticities, the sum of these elasticities, -0.3985 (0.1691), is not less than or equal to negative one. This finding implies that the deduction is treasury inefficient in the long-run.

When the scope of analysis is expanded to accommodate neutrality, the sum of this year's income and price elasticities is -0.9935 (0.1313). This means that in the
short-run, donors are much more responsive to price-reducing charitable deductions than they are to income-reducing tax payments. Thus, increases in marginal tax rates stimulate donors' short-run giving. When neutrality is expanded to include last year's, this year's, and next year's income and price elasticities, the sum of these elasticities is 0.0190 (0.1964). This implies that in the long-run, donors are just as responsive to price-reducing charitable deductions as they are to income-reducing tax payments. In other words, within a three-year window, donors do not change their total contributions, they simply manipulate the timing of these contributions in such a way as to neutralize changes in marginal tax rates.

In the short-run, these findings imply that nonprofit managers will have to find alternative resources in order to maintain customary levels of goods and services. Further, because the deduction is efficient, policy makers have a case for retaining the charitable deduction. In the long-run, nonprofit managers can count on a steady source of funding. Further, policy makers have a case for seeking out alternatives which provide an efficient subsidy. Finally, besides providing a harmonizing link to the traditional literature, these findings provide an interesting contrast to those reported in prior panel studies and underscore the

Concluding Remarks
importance of reexamining model specification and estimation. Although the dynamic two-way fixed-effects model dominates rival models on statistical, specification, and a priori theoretical grounds, it still suffers from violations of underlying statistical assumptions. This implies that the dynamic model's elasticity estimates may be biased and thus unable to provide reliable insights into theoretical relationships. However, the large sample utilized in this study may cause pragmatically irrelevant statistical violations to be statistical significant. At worst, the violations of this model are no more severe than those associated with the econometric models employed in prior research (see Appendix A for additional details).

5.2 Limitations.

The scope of this study is narrowly restricted to the deduction's efficiency and the neutrality of taxes. Clearly, there are other compelling policy and behavioral considerations. For example, how equitable is the deduction across taxpayers and charity sectors? Relative to the charitable deduction, do alternatives, such as floors, credits, ceilings, etc., achieve more desirable levels of efficiency while simultaneously neutralizing donors'
behavioral response to tax changes? What impact does inter-donor feedback have on giving? Does one donor's generosity 'crowd out' another's, so that cross-section and time-series elasticities should differ [Steinberg (1986)]? Can behavioral responses of the recipient charities mitigate the impact of tax change on donations? Does government spending crowd-out donations, so that the deduction is treasury efficient even when the price elasticity is greater than negative one?

Within this study's scope, several issues may restrict the applicability of the findings. First, the data used in this study is taken from itemizing donors' unaudited tax returns.\footnote{Slemrod (1989) concludes that although tax evasion is substantial, use of unaudited data does not significantly bias elasticity estimates. The price elasticity obtained from initially-reported giving is -1.53; from audited giving -1.70. Corresponding income elasticities are 0.34 and 0.26.} Second, nonitemizers and borderline itemizers are noticeably absent from this study's sample.\footnote{See footnote 58 (page 79) and Section 3.1.3, The sample, for a discussion dealing with these donors' lack of representation.} Third, restricting the sample to donors who itemize in every year of the panel prevents estimation algorithms from accessing all available information on itemizing donors. This oversight may introduce attrition or self-selection bias based on ability to itemize.

Other issues may threaten the reliability of the
elasticity estimates underlying the efficiency and neutrality findings. Although able to dominate its static and dynamic rivals on statistical adequacy grounds, the dynamic two-way fixed-effects model of giving still suffers from violations of underlying statistical assumptions. However, the large sample utilized in this study may cause pragmatically irrelevant statistical violations to be statistically significant. This possibility cannot be fully assessed until the parameter estimates of this study's estimable models are recomputed using probability distributions capable of dealing with the thick-tailed distributions generated by the data-generating mechanism (see Appendix A for additional details).

In addition, to the extent that conventional surrogates fail to capture the economic substance of theoretical constructs, parameter estimates may imperfectly reflect true causal relationships. A better feel for this limitation can be obtained once estimable models are identified which do not violate underlying statistical assumptions.

Finally, although robust, the dynamic two-way fixed-effects estimator is conditional on the sample and thus does

---

51 Please see Section 3.1 for a discussion of conventional surrogates and their limitations. In particular, please see footnote 37 (page 63) for a discussion of the adjustments that would be required in order to obtain the best tax-return surrogate for disposable income. Footnote 38 (page 66) is also noteworthy because it addresses Reece and Ziechang's maximum-likelihood alternative to first-dollar price.

Concluding Remarks
not support inferences extended to the population of donors. The conditional or the sample-specific nature of fixed-effects is especially noticeable in a forecasting environment. Predictions for donors and time periods absent in the original estimation are of questionable value since there are no donor- and time-specific effects to accommodate these out-of-sample observations. However, because the individuals examined in this study constitute a large random sample of middle-class itemizing donors, the statistical insights generated by the dynamic two-way fixed-effects model are likely to generalize to other such groups.

5.4 Extensions.

The extensions to this study are practical and flow naturally from the limitations noted above. Imposing a student's t distribution on this study's estimable models should increase the likelihood of obtaining statistically adequate models.\textsuperscript{82} These models may then be used as a basis

\textsuperscript{82}Unfortunately, alternative statistical models such as the student's t are not easily estimated with contemporary statistical packages (SAS and LIMDEP). However, researchers at Virginia Tech are nearing the completion of a statistical package capable of imposing the Student's t distribution on this study's estimable models. Once complete, assessing the sensitivity of parameter estimates to the Student's t distribution is one of the most interesting extensions of this study.
for evaluating the extent to which statistical violations bias elasticity estimates and determining taxation's behavioral implications. Once the 'best' statistically adequate model of giving has been identified, the sensitivity of this model's parameter estimates to more economically sound surrogates for theoretical constructs and the utilization of an unbalanced panel may be assessed.
APPENDIX A:
DETERMINING WHICH MODEL OF CHARITABLE GIVING DOMINATES ITS RIVALS ON STATISTICAL ADEQUACY GROUNDS

A.1 Overview.

Figure A.1 presents a sketch of Spanos's econometric-modeling methodology. The influence of Hsiao's monograph becomes apparent when model specification is discussed below. As applied to this study, the key objective of Spanos's methodology is to provide a good-faith explanation of the data-generating mechanism underlying observable evidence of donors' charitable giving. Consumer theory provides an organizing framework for accomplishing this objective. In its conventional form, consumer theory's idealized description yields the following generalized formulation of donors' demand for giving:

\[
\text{Charitable Giving} = f(\text{Disposable Income, Price}) \quad (A1)
\]

Imposing a log-linear functional form upon this general formulation yields the estimable or traditional (static) model of giving that appears in equation (1). With an orientation towards the estimable model, the probabilistic formulation of the statistical model faithfully represents the data generating mechanism only when providing an adequate summary
Appendix A
of the observed data. Evaluation of 'adequacy' usually requires an iterative process consisting of estimation, tests of statistical adequacy, reparametrization, and model selection (specification adequacy). Once identified, the 'best' adequate model of giving provides the point of reference for meaningful tests of research hypotheses.

When an estimable model fails to adhere to underlying statistical assumptions, an interesting dilemma arises over how to proceed. Resolution of this dilemma depends upon the underlying motivation for undertaking the analysis. If the motivation for the analysis is solely to legitimize a particular theoretical orientation, any one of several ad hoc techniques may artificially harmonize data and theory. For example, suppose that a particular estimable model reflects the conventional theoretical orientation of consumer theory; this year's giving is solely a function of this year's price and disposable income. Further, suppose that the initial estimation of this model violates the assumption of homoskedasticity, independence, or normality. Introducing a model with heteroskedastic disturbances, autocorrelated disturbances, or eliminating outliers forces the data to appear well behaved, generate unbiased estimates, and provide empirical support for a static model of giving. However, harmonization of this type may greatly jeopardizes discovery

Appendix A
of an adequate explanation of the data-generating mechanism underlying observable evidence of donors' giving.

If providing a good-faith explanation of the data-generating mechanism is the motivation for the analysis, violations of statistical assumptions simply indicate that the conventional estimable model fails to consider some important information. This oversight may be due to an overly restrictive theoretical orientation or the selection of an inadequate probability distribution for summarizing the data and making inferences to the population. In the case of charitable giving, consumer theory's habit persistence and life cycle arguments suggest that giving is a dynamic activity. This implies that the static estimable model ignores important information contained in donors' habit persistence tendencies, last year's price and disposable income, and next year's price and disposable income. Notice, this argument does not abandon consumer theory's theoretical framework in favor of brut empiricism. Rather, this argument encourages researchers to more fully exploit the explanatory power of consumer theory.

Income and other closely related distributions, such as charitable contributions and price, are notoriously thick-tailed. The incremental information giving rise to these thick-tailed distributions often proves to be troublesome when the normal probability distributions is used to summarize the data and make inference to the population.
Acting upon this conviction, an iterative process is undertaken to determine what impact this incremental information has on statistical adequacy. This process begins by assessing the statistical adequacy of the traditional static model of giving. In the second stage, donor-specific effects are introduced to control for differences in donors' utility functions. In the third stage, time-specific effects are then added to account for the unique but constant influence that each time period exerts upon charitable giving. In the fourth stage, lagged variables on contributions, income, and price and lead variables on income and price are introduced. The resulting dynamic model of giving also includes donor-specific effects. Finally in the last stage, time-specific effects are added to the dynamic model of giving. At each of these stages, tests of statistical adequacy are conducted in order to determine if each additional piece of information enhances statistical adequacy. The model which achieves the highest level of statistical adequacy is said to dominate its rivals on statistical adequacy grounds.

Once statistical adequacy has been assessed, tests of specification adequacy are undertaken to determine which model of giving provides the best explanation of this year's giving. The model providing this explanation is said to dominate its
rivals on specification grounds. When each of the elasticities motivated by the logically dominant or dynamic version of consumer theory is included in the dominant specification model and proves to be significant and appropriately signed, then this particular model is said to dominate its rivals on a priori theoretical grounds.

A.2 Evaluating statistical adequacy.\textsuperscript{84}

As seen in Figure A.2, two sets of estimable models are examined for statistical adequacy. Static models of giving reflect a synergistic blend of Hsiao's statistical panel-data models and the conventional version of consumer theory permeating the traditional literature. Similarly obtained, dynamic models reflect a richer utilization of consumer theory.

A.2.1 Static models of giving.

Hsiao's panel-data monograph suggests several panel-data reparametrizations for the traditional model appearing in equation (1). The initial panel-data refinement introduces

\textsuperscript{84} In order to find the test statistics appearing in Appendix A and Appendix B, I drew liberally from Greene (1990b), Judge (1985), Kmenta (1986), Maddala (1988), Pindyck and Rubinfeld (1981), and Spanos (1986).

Appendix A
ASSUMPTIONS: HOMOSKEDASTICITY, INDEPENDENCE, LINEARITY, NORMALITY, AND PARAMETER STABILITY

STATIC MODELS OF GIVING

CROSS-SECTIONAL MODEL

PANEL-DATA MODELS

ONE-WAY FIXED-EFFECTS MODEL

ONE-WAY RANDOM-EFFECTS MODEL

TWO-WAY FIXED-EFFECTS MODEL

TWO-WAY RANDOM-EFFECTS MODEL

NO STATISTICALLY ADEQUATE MODEL

DYNAMIC MODELS OF GIVING

PANEL-DATA MODELS

ONE-WAY FIXED-EFFECTS MODEL

ONE-WAY RANDOM-EFFECTS MODEL

TWO-WAY FIXED-EFFECTS MODEL

TWO-WAY RANDOM-EFFECTS MODEL

NO STATISTICALY ADEQUATE MODEL

SELECTION OF 'BEST' STATISTICALLY ADEQUATE MODEL OF GIVING

FIGURE A.2 ASSESSING STATISTICAL ADEQUACY
time-invariant donor-specific constants, $\beta_{0i}$. These parameters reflect the unique but constant impact each donor's characteristics has upon charitable giving. This reparametrization produces the one-way (donor-specific) fixed-effects panel-data model:

$$\ln \text{ Contribution}_{it} = \beta_{0i} + \beta_1 (\ln \text{ Income}_{it}) + \beta_2 (\ln \text{ Price}_{it}) + \beta_3 (\text{ Marital Status}_{it}) + \beta_4 (\text{ Age}_{it}) + \beta_5 (\text{ Dependents}_{it}) + e_{it} \quad (A2)$$

Notice, explicit recognition is now given to the time observations on each donor, $i$.

By portraying each donor-specific effect as a time-invariant realization of the random error term, $\tau_i$, the one-way fixed-effects model is transformed into the following one-way random-effects model:

$$\ln \text{ Contribution}_{it} = \beta_0 + \beta_1 (\ln \text{ Income}_{it}) + \beta_2 (\ln \text{ Price}_{it}) + \beta_3 (\text{ Marital Status}_{it}) + \beta_4 (\text{ Age}_{it}) + \beta_5 (\text{ Dependents}_{it}) + \tau_i + e_{it} \quad (A3)$$

Unlike its fixed-effects counterpart, conclusions drawn from parameter estimates of the random-effects model are imputable to the population of donors if donor-specific effects are uncorrelated (orthogonal) with the regressors.

The addition of time-specific effects transforms these...
one-way panel-data models into two-way models. Like its one-way counterpart, the two-way fixed-effects model treats time-specific effects, $\tau_t$, as constants. These parameters reflect the unique but constant impact each time period has upon donors' giving. The two-way fixed-effects model is specified as follows:

$$\ln \text{Contribution}_{it} = \alpha_0 + \beta_0i + \tau_t + \beta_1 (\ln \text{Income}_{it}) + \beta_2 (\ln \text{Price}_{it}) + \beta_3 (\text{Marital Status}_{it}) + \beta_4 (\text{Age}_{it}) + \beta_5 (\text{Dependents}_{it}) + e_{it} \quad (A4)$$

Where $\alpha_0$ is a common intercept.

By treating each time-specific effect as a realization of the random error term, $v_t$, the two-way fixed-effects model is transformed into this two-way random-effects model:

$$\ln \text{Contribution}_{it} = \beta_0 + \beta_1 (\ln \text{Income}_{it}) + \beta_2 (\ln \text{Price}_{it}) + \beta_3 (\text{Marital Status}_{it}) + \beta_4 (\text{Age}_{it}) + \beta_5 (\text{Dependents}_{it}) + \pi_i + v_t + e_{it} \quad (A5)$$

Like its one-way counterpart, imputability to the population of donors is possible if donor-specific and time-specific effects are uncorrelated (orthogonal) with the regressors.

A.2.2 Dynamic models of giving.

Consumer theory's habit persistence and life cycle
arguments motivates several 'new' elasticity constructs which transform giving into a dynamic activity. This depiction is especially appealing when observable realizations of the data-generating mechanism reflect a time dimension and/or emanate from the same donors. Given the operational counterparts introduced in Chapter 3 and allowing for donor-specific effects, the dynamic one-way fixed-effects model is:

\[
\ln \text{Contribution}_{it} = \beta_{0i} + \beta_1 (\ln \text{Contribution}_{it-1}) + \\
\beta_2 (\ln \text{Income}_{it-1}) + \beta_3 (\ln \text{Price}_{it-1}) + \\
\beta_4 (\ln \text{Income}_{it}) + \beta_5 (\ln \text{Price}_{it}) + \\
\beta_6 (\text{Marital Status}_{it}) + \beta_7 (\text{Age}_{it}) + \\
\beta_8 (\text{Dependents}_{it}) + \beta_9 (\ln \text{Income}_{it+1}) + \\
\beta_{10} (\ln \text{Price}_{it+1}) + \epsilon_{it} \quad \text{(A6)}
\]

The dynamic one-way random-effects, two-way fixed-effects, and two-way random-effects versions of this model are obtained in exactly the same manner as their static-model counterparts. These models also offer the same incremental informational refinements that they did in the static setting. Consequently, these models are not shown explicitly.

### A.2.3 Statistical adequacy tests.

Several diagnostic tests are used to evaluate the statistical adequacy of each estimable model of giving. These tests reveal whether a given estimable model adheres to
underlying statistical assumptions of homoskedasticity, independence, linearity, normality, and parameter stability. If static and/or dynamic models of giving are statistically inadequate, the integrity of the test statics underlying the evaluation of research hypotheses may be compromised.

**Homoskedasticity.** The homoskedasticity of error terms is evaluated with the RESET test [Ramsey (1969)]. This test focuses on departures from homoskedasticity by testing to see if error variance is dependent upon the conditioning information found in the original regressors. The test statistic is based on the auxiliary regression:

\[ e_i^2 = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_n x_{ni} + \tau_2 y_i^2 + \tau_3 y_i^3 + u_i \] (A7)

The variables \( e_i, x_{1i}, \ldots, x_{ni}, \) and \( y_i \) are, respectively, the residuals, regressors, and fitted values originating from either static or dynamic models of giving. The following hypotheses facilitate evaluation of homoskedasticity:

**HA1**

Estimation of a given static or dynamic model of giving does not give rise to homoskedastic error terms.

---

The number of allowed regressors in a panel-data setting are limited by LIMDEP. The limitation criterion is a function of the number of donors in the sample. Because this study's sample has 1,382 donors, LIMDEP would not permit estimation of the model needed for utilizing White's test [White (1980)]. Thus, as a matter of convenience, the RESET test was used. Because the White test is more exhaustive, it will detect violations of homoskedasticity when the RESET does not. This should not be a problem in this study because the RESET test rejects the assumption of homoskedasticity for each of this study's estimable models.

**Appendix A**
That is, \( \beta_0 = \beta_1 = \ldots = \beta_n = \tau_2 = \tau_3 = 0 \).

**HA\(^1\)_1:** Estimation of a given static or dynamic model gives rise to heteroskedastic error terms, suggesting at least one coefficient, \( \beta_0, \beta_1, \ldots, \beta_n, \tau_2 \), and/or \( \tau_3 \) is not equal to zero.

The test statistic is computed as follows:

\[
F = \begin{bmatrix} \frac{N - K - 1}{K} \frac{SSR}{SSE} \end{bmatrix}^{-1} F(N - K - 1) \quad (A8)
\]

SSR is sum of squares regression, SSE is sum of squares error, \( K \) is the number of regressors (not including the intercept), and \( N \) is the number of observations.

**Independence.** A test statistic based on the following auxiliary regression reveals if autocorrelation is present:

\[
\hat{e}_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_n x_{ni} + \phi \hat{e}_{i-1} + u_i \quad (A9)
\]

These hypotheses facilitate evaluation of independence:

**HA\(^2\)_0:** Estimation of a given static or dynamic model of giving does not violate independence. That is, \( \phi = 0 \).

**HA\(^2\)_1:** Estimation of a given static or dynamic model of giving gives rise to autocorrelated error terms. That is, \( \phi \) is not equal to zero.

This two-sided test statistic discriminates between these competing hypotheses:

\[
\frac{\hat{\phi} - 0}{\sqrt{t_{N - K - 1}}} \quad (A10)
\]

\[
\text{[ VARIANCE } \hat{\phi} ]^{1/2}
\]

Appendix A
**Linearity.** The assumption of linearity is tested using a minor variation of the RESET test. This test statistic is based on the auxiliary regression:

$$
\hat{e}_i = \beta_0 + \beta_1 x_{1i} + \ldots + \beta_n x_{ni} + \tau_2 \hat{y}_{i1}^2 + \tau_3 \hat{y}_{i1}^3 + u_i \tag{A11}
$$

This auxiliary regression uses residuals as the dependent variable. The following hypotheses facilitate evaluation of linearity:

**HA3_0:** The transformed (logged) charitable contributions are linear functions of donors' transformed (logged) disposable income and price of giving and marital status, age, and dependents. That is, \( \tau_2 = \tau_3 = 0 \).

**HA3_1:** The transformed (logged) charitable contributions are nonlinear functions of donors' transformed (logged) disposable income and price of giving and marital status, age, and dependents. That is, \( \tau_2 \) and/or \( \tau_3 \) are (is) not equal to zero.

The appropriate test statistic is computed as follows:

$$
F = \left[ \frac{N - K - 1}{R} \right] \left[ \frac{\text{RSSE} - \text{USSE}}{\text{USSE}} \right]^{\cdot} F(R, N - K - 1) \tag{A12}
$$

\text{RSSE} is the restricted sum of squared errors appearing in the original static or dynamic model being examined, \text{USSE} is the unrestricted sum of square errors, and \( R \) represents the number of restrictions that separate the restricted model from its unrestricted rival. In this case, there are two restrictions.

Appendix A
because the squared and cubed fitted values did not appear as regressors in either the original static or dynamic models of charitable giving.

**Normality.** D'Agostino and Pearson's parametric omnibus statistic provides a powerful and informative test for detecting deviations from normality due to skewness and/or kurtosis [e.g., D'Agostino, Belanger, and D'Agostino (1990)]. The following set of competing hypotheses provide a framework for determining whether the assumption of normality is violated:

\[ H_{A0}: \text{The underlying population from which the sample is drawn is normally distributed. That is, the third (skewness) and fourth (kurtosis) sample moments are respectively zero and three.} \]

\[ H_{A1}: \text{The underlying population from which the sample is drawn is not normally distributed. That is, the underlying population distribution suffers from nonnormality due to skewness (the third sample moment is not equal to zero) and/or kurtosis (the fourth sample moment is not equal to three).} \]

The following test statistic is relevant:

\[
K^2 = (Z(b_1)^{1/2})^2 + (Z(b_2))^2 - X_2^2 \tag{A13}
\]

where, \((b_1)^{1/2}\) and \(b_2\) are, respectively, the third and fourth sample moments and the terms \((Z(b_1)^{1/2})\) and \((Z(b_2))\) are the normal approximations of \((b_1)^{1/2}\) and \(b_2\).\(^{86}\)

\(^{86}\)The term \((Z(b_1)^{1/2})\) is obtained in the following manner:

1. Using the residuals, \(^\hat{u}\), from the estimation of equation (12), compute \((b_1)^{1/2}\) as follows:

Appendix A 142
2. Then compute:

\[ Y = (b_1)^{1/2} \left[ (n + 1)(n + 3) \over 6(n - 2) \right]^{1/2} \]

\[ \theta_2(b_1)^{1/2} = \frac{3(n^2 + 27n - 70)(n + 1)(n + 3)}{(n - 2)(n + 5)(n + 7)(n + 9)} \]

\[ u^2 = -1 + \left( 2(b_2(b_1)^{1/2} - 1) \right)^{1/2} \]

\[ \delta = 1 + \ln(u)^{1/2} \quad \text{and} \quad \alpha = \left( 2 + (u^2 - 1) \right)^{1/2} \]

3. Finally, compute: \[ \Xi((b_1)^{1/2}) = \delta \ln((Y + \alpha) + [(Y + \alpha)^2 + 1]^{1/2}) \]

The term \( \Xi(b_2) \) is obtained in the following manner:

1. Using the residuals, \( u_i \), from the estimation of equation (12), compute \( b_2 \) as follows:

\[ \left[ \frac{1}{n} \sum_{i=1}^{n} u_{i}^2 \right]^{1/2} + \left[ \frac{1}{n} \sum_{i=1}^{n} u_{i}^2 \right] \]

2. Then compute \( b_2 \)'s mean and variance:

\[ \mathbb{E}(b_2) = \frac{3(n - 1)}{(n + 1)} \quad \text{and} \quad \text{Var}(b_2) = \frac{24n(n - 2)(n - 3)}{(n + 1)^2(n + 3)(n + 5)} \]

3. Next compute the standardized version of \( b_2 \):

\[ X = (b_2 - \mathbb{E}(b_2)) + (\text{Var}(b_2))^{1/2} \]

4. Now compute \( b_2 \)'s third standardized moment:

\[ (\mathbb{E},_2(b_2))^{1/2} = \frac{6(n^2 - 5n + 2)}{(n + 7)(n + 9)} \left[ \frac{6(n + 3)(n + 5)}{n(n - 2)(n - 3)} \right]^{1/2} \]

5. Then compute:

\[ A = 6 + \frac{8}{(\mathbb{E},_2(b_2))^{1/2}} \left[ \frac{2}{(\mathbb{E},_2(b_2))^{1/2}} + \left[ 1 + \frac{4}{(\mathbb{E},_2(b_2))^{1/2}} \right]^{1/2} \right] \]

Appendix A
**Parameter Stability.** The stability of parameter estimates is examined across four potentially problematic dimensions: 1) Time; 2) Space; 3) Disposable income levels, and 4) Tax sophistication. An evaluation of the stability of parameter estimates across time is carried out by partitioning the restricted panel into two equal time periods. Parameter estimates are then generated from each of these time periods. Evaluation of parameter stability across time is facilitated with the following hypotheses:

\[ H_{A5_0}: \text{Parameter estimates generated from the first time period are no different from those generated from the second time period.} \]

\[ H_{A5_1}: \text{At least one of the parameter estimates generated from the first time period differs from its second time-period counterpart.} \]

The following test-statistic estimator is relevant:

\[
F = \left[ \frac{N_1 + N_2 - 2K - 2}{K + 1} \right] \left[ \frac{RSE - USSE}{USSE} \right] - f((K + 1), (N_1 + N_2 - 2K - 2)) \quad (A14)
\]

An evaluation of the stability of parameter estimates across space is accomplished by taking the balanced panel and

---

6. Finally, compute:

\[
Z(b_2) = \left[ \frac{1 - \frac{2}{9(A)}}{1 + \frac{1 - (2 + A)}{1 + x(2 + (A - 1))^{1/2}}} \right]^{1/3} + \left[ \frac{2}{9(A)} \right]^{1/2}
\]

Now, substitute \(Z(b_1)^{1/2}\) and \(Z(b_2)\) into equation (A13). When these standardized moments are squared and summed, the resulting test statistic is distributed Chi Square with two degrees of freedom.

**Appendix A**

144
partitioning its donors into two equal subsets.\footnote{The term \textit{space} is used as a catchall for any unobserved dimension impairing stability of parameter estimates.} One subset contains observations on the first 691 donors in this study’s sample. The other subset contains observations on the last 691 donors. Parameter estimates are then generated from each of these subsets. The following hypotheses facilitate evaluation of parameter stability across space:

\begin{align*}
\text{HA}_6^0: & \quad \text{Parameter estimates generated from observations on the first 691 donors are no different from those generated from observations on the last 691 donors.} \\
\text{HA}_6^1: & \quad \text{At least one of the parameter estimates generated from the first subset of donors differs from its second-subset counterpart.}
\end{align*}

The statistical comparison of the parameter estimates generated from these two donor subsets is based upon a test statistic derived using equation (A14).

Evaluation of parameter stability across income levels is carried out by introducing interactive dummy variables to account for three levels of disposable income. Because this study’s restricted panel is made up predominantly of middle-class itemizing donors, the interactive dummy variables partition these donors into lower-middle, middle-middle, and upper-middle classes. Donors whose disposable income is less than or equal to $30,000 are assigned to the lower-middle
class. Donors whose disposable income is greater than $30,000 and less than or equal to $50,000 are assigned to the middle-middle class. Donors whose disposable income is greater than $50,000 are assigned to the upper-middle class. Please note that these interactive dummy variables do not indicate which donors are always in the lower-, middle-, or upper-middle class. Instead, these interactive dummy variables indicate when donors switch from one middle-income class to another. That is, the question being asked here is whether a change in donors' middle-income class status alters their responsiveness to changes in disposable income and price.

Although similar models exist for each of the other static and dynamic models of giving, consider the case of the traditional model of giving. The addition of interactive income dummy variables gives rise to the following model:

\[
\ln \text{Contribution}_{i} = \beta_0 + \beta_1 (\ln \text{Disposable Income}_{i}) + \beta_2 (\ln \text{Price}_{i}) + \beta_3 (\text{Marital Status}_{i}) + \\
\beta_6 (\text{Age}_{i}) + \beta_7 (\text{Dependents}_{i}) + \beta_6 (\ln \text{Disposable Income}_{i} \times \text{Mid-Mid-Cls}_{i}) + \\
\beta_7 (\ln \text{Disposable Income}_{i} \times \text{Up-Mid-Cls}_{i}) + \beta_8 (\ln \text{Price}_{i} \times \text{Mid-Mid-Cls}_{i}) + \\
\beta_9 (\ln \text{Price}_{i} \times \text{Up-Mid-Cls}_{i}) + \epsilon_i
\] (A15)

A note on model interpretation is appropriate. If a given observation reflects a lower-middle-class donor, the interactive dummy variables associated with \( \beta_6, \beta_7, \beta_8, \) and \( \beta_9 \) become zero and equation (A15) collapses to the traditional model appearing in equation (1). To contrast, if a given observation reflects an upper-middle-class donor, the

Appendix A
interactive variable associated with $\beta_6$ and $\beta_8$ become zero, thus disappearing from the modified estimation model. The following hypotheses facilitate evaluation of parameter stability across income classes:

$H_{A7_0}$: Interactive income dummy variables are devoid of information, implying $\beta_6 = \ldots = \beta_3 = 0$.

$H_{A7_1}$: At least one interactive dummy variable has information content, suggesting parameter instability exists.

The test statistic is generated from equation (A14).

The details of evaluating parameter stability across donors' tax sophistication are not provided because they are nearly identical to those utilized when assessing parameter stability across income classes. Instead, attention is focused upon the role of the tax-sophistication dummy variable. This interactive dummy variable takes on a value of zero if donors' contributions are made up solely of cash and zero otherwise. Donors whose contributions are made up solely of cash are assumed to have less tax sophistication than donors whose contributions include noncash gifts. Donors whose contributions include noncash gifts have to deal with documentation, valuation, and long-term capital gain issues. Consequently, these donors either have a higher awareness of the tax law than their cash-only counterparts or rely upon knowledgeable professionals.

Appendix A

Tables A.1 and A.2 contain a collection of the test statistics generated while evaluating the statistical adequacy of each of the static and dynamic models examined in this study. Please note that each statistical assumption is cross-referenced to the set of competing hypotheses that provides the framework for determining whether violations exist. The reference made to each set of competing hypotheses also assists the reader in identifying the motivating paragraphs in Section A.2.3 that legitimize these hypotheses.

Each of the test statistics appearing in Tables A.1 and A.2 are reported relative the critical values associated with a probability value of 1 percent. In order to facilitate the reader's utilization of these Tables, consider the following example. Because the $F_{7,11048}$ test statistic of 15.19 exceeds its applicable critical value of 2.64, the pooled or cross-sectional model violates the assumption of homoskedasticity. Similar findings are obtained for the assumptions of independence (test statistic 127.25 versus critical value 2.58), linearity (34.16 versus 4.61), and normality (1,639.12 versus 9.21). In addition, the pooled model violates the assumption of parameter stability across time (12.74 versus 2.80), space (14.24 versus 2.80), income (21.96 versus 3.32),
<table>
<thead>
<tr>
<th>MODEL</th>
<th>HOMOSCE-</th>
<th>INDEPEND-</th>
<th>LINEA-</th>
<th>NORMA-</th>
<th>PARAMETER STABILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>COMPETING</td>
<td>DASTICITY</td>
<td>ENCE</td>
<td>RITY</td>
<td>ALITY</td>
<td>STABILITY</td>
</tr>
<tr>
<td>HYPOTHESES:</td>
<td>H0 VS</td>
<td>H0 VS</td>
<td>H0 VS</td>
<td>H0 VS</td>
<td>H0 VS VS VS VS</td>
</tr>
<tr>
<td>CROSS-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SECTIONAL TEST</td>
<td>15.19</td>
<td>34.16</td>
<td>1639.12</td>
<td>12.74</td>
<td>282.40</td>
</tr>
<tr>
<td>STATISTIC</td>
<td>VS 2.64</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 2.80</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 2.80</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>F_{7,11048}</td>
<td>t_{9667}</td>
<td>F_{2,11048}</td>
<td>X _ _ _</td>
<td>F_{6,11044}</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
</tr>
<tr>
<td>ONE-WAY FIXED-</td>
<td>3.46</td>
<td>1.15</td>
<td>2230.68</td>
<td>2.62</td>
<td>292.86</td>
</tr>
<tr>
<td>EFFECTS TEST</td>
<td>VS 1.00</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>F_{1386,9668}</td>
<td>t_{8286}</td>
<td>F_{2,9667}</td>
<td>X _ _ _</td>
<td>F_{1386,9264}</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>OK</td>
<td>VIOLATES</td>
<td>OK</td>
</tr>
<tr>
<td>ONE-WAY RANDOM-</td>
<td>7.66</td>
<td>37.96</td>
<td>1593.48</td>
<td>28.21</td>
<td>281.19</td>
</tr>
<tr>
<td>EFFECTS TEST</td>
<td>VS 2.64</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 2.80</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 2.80</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>F_{7,11048}</td>
<td>t_{9667}</td>
<td>F_{2,11048}</td>
<td>X _ _ _</td>
<td>F_{6,11044}</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
</tr>
<tr>
<td>TWO-WAY FIXED-</td>
<td>3.53</td>
<td>1.18</td>
<td>2321.04</td>
<td>2.51</td>
<td>229.02</td>
</tr>
<tr>
<td>EFFECTS TEST</td>
<td>VS 1.00</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
<td>VS 4.61</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>F_{1396,9659}</td>
<td>t_{8277}</td>
<td>F_{2,9658}</td>
<td>X _ _ _</td>
<td>F_{1394,8274}</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>OK</td>
<td>VIOLATES</td>
<td>OK</td>
</tr>
<tr>
<td>EFFECTS RANDOM-EFFECTS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Appendix A
and taxpayer sophistication (282.40 versus 4.61). In summary, the pooled model violates each of its underlying statistical assumptions.

Similar findings are obtained when this process of evaluation is applied to each of the remaining static and dynamic models. In particular, with the exceptions of linearity and parameter stability across space, the static one-way fixed-effects model also violates each of its underlying statistical assumptions. Surprisingly, every one of the underlying statistical assumption is violated by the static one-way random-effects model. Finally, the two-way fixed-effects model is only able to satisfy the assumptions of linearity and parameter stability across space and income.

The story is much the same for the dynamic model of giving. With the exception of independence and parameter stability across time, the dynamic one-way fixed-effects model violates everyone of its underlying statistical assumptions. The one-way random-effects model is only able to satisfy the assumptions of parameter stability across time and space. Finally, with the exception of parameter stability across space, the two-way fixed-effects model also violates each of its underlying statistical assumptions. 88

88 For the reasons noted in Tables A.1 and A.2, estimation of the static and dynamic two-way random-effects models failed.
<table>
<thead>
<tr>
<th>MODEL</th>
<th>HOMOSCE-</th>
<th>INDEPEND-</th>
<th>LINEARITY</th>
<th>NORMALITY</th>
<th>PARAMETER STABILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>ONE-WAY</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td>VS</td>
<td></td>
</tr>
<tr>
<td>FIXED-EFFECTS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TEST STATISTIC</td>
<td>2.84</td>
<td>2.28</td>
<td>13.17</td>
<td>2077.87</td>
<td>2.01</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 1.0</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>$t_{5517}$</td>
<td>$t_{5517}$</td>
<td>$X_{2}^{2}$</td>
<td>$F_{1391,5510}$</td>
<td>$F_{1391,5510}$</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &gt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &gt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>OK</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
</tr>
<tr>
<td>ONE-WAY</td>
<td>36.93</td>
<td>-27.42</td>
<td>80.93</td>
<td>2243.54</td>
<td>1.00</td>
</tr>
<tr>
<td>RANDOM-EFFECTS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TEST STATISTIC</td>
<td>VS 2.18</td>
<td>VS -2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 2.25</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 2.18</td>
<td>VS -2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 2.25</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>$F_{12,8279}$</td>
<td>$t_{698}$</td>
<td>$F_{11,8270}$</td>
<td>$F_{14,8267}$</td>
<td>$F_{7,8274}$</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>OK</td>
<td>VIOLATES</td>
</tr>
<tr>
<td>TWO-WAY</td>
<td>2.85</td>
<td>2.72</td>
<td>11.57</td>
<td>2075.02</td>
<td>1.99</td>
</tr>
<tr>
<td>FIXED-EFFECTS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TEST STATISTIC</td>
<td>VS 1.00</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
</tr>
<tr>
<td>VS CRITICAL VALUE</td>
<td>VS 1.00</td>
<td>VS 2.58</td>
<td>VS 4.61</td>
<td>VS 9.21</td>
<td>VS 1.00</td>
</tr>
<tr>
<td>DISTRIBUTION</td>
<td>$F_{1397,5503}$</td>
<td>$t_{5510}$</td>
<td>$F_{1397,5503}$</td>
<td>$F_{1397,5503}$</td>
<td>$F_{1397,5503}$</td>
</tr>
<tr>
<td>P VALUE</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
<td>P &lt; 0.01</td>
</tr>
<tr>
<td>CONCLUSION</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>VIOLATES</td>
<td>OK</td>
</tr>
<tr>
<td>TWO-WAY</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RANDOM-EFFECTS</td>
<td>INSUFFICIENT DEGREES OF FREEDOM ARE AVAILABLE FOR COMPUTING PARAMETERS IN THE TIME DIMENSION. FOR THIS REASON, ESTIMATION OF THE TWO-WAY RANDOM-EFFECTS MODEL FAILED.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
A careful examination of Tables A.1 and A.2 shows that even though each of the static and dynamic models are statistically inadequate, distinct differences exist in their overall levels of inadequacy. A simple ranking scheme highlights these differences and, thus facilitates a discussion of why they exist. To facilitate analysis, this ranking scheme is applied simultaneously to both static and dynamic models. The results appearing in Table A.3 reveal that each static and dynamic model is ranked in terms of how badly it violates a given assumption. The relative magnitude of each model's test statistics determines how badly an assumption is violated. For example, consider the assumption of homoskedasticity. Because the dynamic one- and two-way fixed-effects models have essentially equivalent equivalent test statistics of 2.84 and 2.85, respectively, these models come closest to satisfying the assumption of homoskedasticity. Consequently, the first and second place rankings are summed and divided equally between these two models. Thus, these models are each given a rank of 1.5.

---

In order to prevent trivial differences in test statistics from distorting the ranking, nearly equivalent test statistics are treated as ties. For example, when assessing normality, one discovers that the test statistic of the dynamic one-way fixed-effects model, 2,074.87, is essentially the same as the one reported for the dynamic two-way fixed-effects model, 2,077.02. Consequently, a tie results and the rank of 3 and 4 are divided evenly between these two test statistics.
<table>
<thead>
<tr>
<th>MODEL</th>
<th>ASSUMPTIONS</th>
<th>SUMMARY STATISTICS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>HOMOGENEITY</td>
</tr>
<tr>
<td>STATIC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CROSS-SECTIONAL</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>ONE-WAY FIXED-EFFECTS</td>
<td>3.5</td>
<td>3.5</td>
</tr>
<tr>
<td>ONE-WAY RANDOM-EFFECTS</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>TWO-WAY FIXED-EFFECTS</td>
<td>3.5</td>
<td>3.5</td>
</tr>
<tr>
<td>TWO-WAY RANDOM-EFFECTS</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DYNAMIC</th>
<th>DYNAMIC</th>
<th>DYNAMIC</th>
<th>DYNAMIC</th>
<th>DYNAMIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ONE-WAY FIXED-EFFECTS</td>
<td>1.5</td>
<td>1.5</td>
<td>4</td>
<td>3.5</td>
</tr>
<tr>
<td>ONE-WAY RANDOM-EFFECTS</td>
<td>7</td>
<td>5</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>TWO-WAY FIXED-EFFECTS</td>
<td>1.5</td>
<td>1.5</td>
<td>3</td>
<td>3.5</td>
</tr>
<tr>
<td>TWO-WAY RANDOM-EFFECTS</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
The same argument holds for the static one- and two-way fixed-effects models. Consequently, these models are given a rank of 3.5, the average of the third and fourth place rankings. The static one-way random-effects, cross-sectional, and dynamic one-way random-effects models receive rankings of 5, 6, and 7, respectively. The last place ranking of 7 means the dynamic one-way random-effects model has the worst violation of the homoskedasticity assumption.

This ranking process continues until a set of rankings is generated for each statistical assumption. Because parameter stability is really just one assumption, an average of the time, space, income, and tax sophistication rankings is used in computing each model's sum of ranks. Each model's average rank, obtained by dividing its sum of ranks by 5 (the number of statistical assumptions), provides the reference point for assigning each model's final rank.

The final ranking shows that one-way fixed-effects models have much lower levels of statistical inadequacy than cross-sectional and one-way random-effects models. These reductions in statistical inadequacy are attributable to the incremental information contained in donor-specific constants. Relative to their one-way counterparts, two-way fixed-effects models have either equivalent or lower levels of statistical inadequacy. The incremental information contained in time-
specific constants accounts for this additional reduction in statistical inadequacy. In addition, the dynamic two-way fixed-effects model has a much lower level of statistical inadequacy than its static counterpart. That is, the simultaneous utilization of the incremental information contained in donors' habit persistence tendencies, last year's income and price, and next year's income and price enables the dynamic two-way fixed effects to achieve the greatest reduction in statistical inadequacy. Thus, the dynamic two-way fixed-effects model dominates its static and dynamic rivals on statistical adequacy grounds.

Unfortunately, the joint utilization of this incremental information is not quite sufficient to ensure statistical adequacy. Because statistical inadequacy persists despite the exhaustive utilization of the incremental information motivated by this study's theoretical and empirical frameworks, I suspect other forces are at work. This dilemma provides me with a strong incentive to invoke ad hoc techniques to harmonize the data with underlying statistical assumptions.90 However, this strategy forces the data-generating mechanism to fit into informationally inadequate

---

90 In the case of the two-way dynamic fixed-effects model of giving, discarding outliers beyond plus or minus 2.5 standard deviations from the mean eliminates violations of independence, linearity, and normality. However, heteroskedasticity still persists.
estimable models, thus compromising this study's objective of identifying an adequate explanation of the data generating mechanism underlying observable evidence of donors' giving.

A better approach is to examine available empirical evidence for insight into why this statistical inadequacy still lingers. An appeal to Tables A.1 and A.2 reveals that each model examined in this study violates the assumptions of homoskedasticity and normality. The normal approximations of the third and fourth moments generated by D'Agostino and Pearson's test statistics show that normality violations are driven by thick-tailed residuals. The normal probability plot and histogram of the raw residuals generated from the dynamic two-way fixed-effects model strengthen this observation (see Figures A.3 and A.4, respectively).\footnote{Foreshadowing briefly, the dynamic two-way fixed-effects model is used because it dominates its static and dynamic rivals on statistical, specification, and a priori theoretical grounds.}

If these raw residuals are normally distributed, they should correspond closely to those of an idealized normal distribution. When the idealized distribution has a hypothetical residual at -2.5 standard deviations, the distribution of estimated residuals should also have a residual at -2.5 standard deviations. Similarly, if the idealized distribution has a hypothetical residual at -2.45

\begin{center}
\textbf{Appendix A}
\end{center}
Appendix A
standard deviations, the distribution of estimated residuals should have a corresponding estimated residual at -2.45 standard deviations. Carried to its logical conclusion, this matching process yields a straight line emanating from -2.5 (vertical axis) with a slope of negative one. Thus, departures from normality manifests themselves as deviations from this straight line.

In the case of the dynamic two-way fixed-effects model, the normal probability plot looks like a backward S-shaped curve. The curve is formed because the distribution of estimated residuals has several residuals in its tail which have no corresponding residuals in the idealized distribution. To clarify, the estimated residuals at -4.75 standard deviations have no matching residual in the idealized distribution because idealized residuals are quite scarce beyond -2.5 standard deviations. A similar argument holds for the residuals at +4.75. Thus, the outliers from the distribution of estimated raw residuals keep stacking up at both edges of the plot. The resulting backward S-shaped curve is characteristic of thick-tailed residual distributions.

By way of contrast, the normal probability plot and histogram for the standardized residuals of the dynamic two-way fixed-effects model are shown in Figures A.5 and A.6. In an even more dramatic fashion, these depictions of the
Figure A.5 Normal Probability Plot of the Standardized Residuals from the Dynamic Two-Way Fixed-Effects Model

Figure A.6 Histogram of the Standardized Residuals from the Dynamic Two-Way Fixed-Effects Model

Appendix A
standardized residuals reveal the thick-tailedness of the residuals generated from the dynamic two-way fixed-effects model. Roughly 1,000 of the residuals generated by the dynamic two-way fixed-effects model are at or beyond plus or minus 3.0 standard deviations from the mean. These ill-behaved residuals give this distribution its thick-tailed appearance and account for roughly 12 percent \((1,000 / (11,056 - (1,382 \times 6))\) where 11,056 represents the total sample and \((1,382 \times 2)\) represents the degrees of freedom lost when leads and lags are introduced) of the observations contained in the sample. If there is no duplication of donors, elimination of these 'outliers' would drop over 6,000 observations \((1,000 \text{ donors} \times 6 \text{ years per donor})\) observations from the sample. The loss of this much information would clearly hamper a good-faith attempt to explain the data explain the data generating mechanism underlying observable realizations of donors' charitable giving.

Collapsing the problem to a two-dimensional depiction, Figure A.7 provides a link between the normality test's thick-tail finding and the homoskedasticity test's heteroskedastic-residuals finding. If residuals were well-behaved, the plot of residuals by contributions would result in a band of randomly disbursed residuals about the horizontal line emanating from zero. However, this plot shows a systematic
RESIDUALS FROM THE DYNAMIC TWO-WAY FIXED-EFFECTS 4.0 MODEL

LEGEND:
A = 1 OBSERVATION
B = 2 OBSERVATIONS
ETC.

NOTE:
6621 OBSERVATIONS ARE HIDDEN BECAUSE THE LEGEND ONLY ALLOWS A MAXIMUM OF 26 OBSERVATIONS (2) TO APPEAR EXPLICITLY IN THE GRAPH.

THE NATURAL LOG COUNTERPARTS OF DONORS' CONTRIBUTIONS

FIGURE A.7 A PLOT OF RAW RESIDUALS ON DONORS' CONTRIBUTIONS

Appendix A
relationship between the size of a donor's contribution and its accompanying residual. In particular, the dynamic two-way fixed-effects model over-predicts small gifts and under-predicts large gifts. In extreme cases (roughly 1,000 of them) these flawed prediction tendencies take on distortionary proportions, thus generating a thick-tailed residual distribution.

The presence of heteroskedastic and thick-tailed residuals indicates that the normal distribution does not provide an adequate summary of the data-generating mechanism. When data-generating mechanisms generate thick-tailed data distributions, a member of the elliptical symmetric family of distributions may provide an excellent alternative statistical model [Spanos (1990)]. An elliptical distribution, such as Student's \( t \), is able to accommodate the thick-tailed information generated by the charitable-giving data-generating mechanism, because this distribution offers a logically better summarization mechanism, additional reductions in statistical inadequacy are possible.

Unfortunately, alternative statistical models such as the student's \( t \) are not easily estimated with contemporary statistical packages (SAS and LIMDEP).\(^2\) Consequently, it is

\(^2\)Researchers at Virginia Tech are nearing the completion of a statistical package capable of easily imposing the Student's \( t \) distribution on this study's estimable models. Once complete, assessing
difficult to determine the direction and magnitude of the biases caused by statistical violations. It is possible that the large sample used in this study is causing pragmatically irrelevant statistical violations to be statistical significant. At worst, the violations of the dynamic two-way fixed effect model are no more severe than those associated with the econometric models employed in prior research.\textsuperscript{93} For this reason, the results of this study are provided on a 'subject to' basis for those readers who feel classical estimates provide useful approximations.

\textsuperscript{93}Although second best, these "subject to" results are at least as informative as previously reported panel-data, time-series, and cross-sectional results. This 'at least' argument is based on the following observations: 1) Shorter versions of this study's data base have been used as samples in prior panel-data studies; 2) Consistent violation of statistical assumptions linked to the time-series (independence) and cross-sectional (heteroskedasticity) dimensions of this study's data set implicates elasticity estimates generated by prior time-series and cross-sectional analyses, and 3) Explicit attention to statistical adequacy is noticeable absent in the traditional literature.

Appendix A

163
APPENDIX B:
DETERMINING WHICH MODEL DOMINATES
ITS RIVALS ON SPECIFICATION ADEQUACY GROUNDS

B.1 Evaluating Specification Adequacy.

Having addressed statistical adequacy issues, tests of specification are now of interest. Within the framework of consumer theory, the objective of these specification adequacy tests is to identify the model which provides the best explanation of the data. Figure B.1 illustrates the research design for determining the 'best' model of giving. The first set of analyses identifies the 'best' static model of giving. The 'best' dynamic model of giving is revealed by the second set of analyses. The final analysis discloses the 'best' overall model of giving.

The initial static-model comparisons contrast the one- and two-way fixed- and random-effects models. Once shown to be statistically adequate, random-effects estimators offer meaningful alternatives if they are not misspecified relative to their fixed-effects counterparts. These hypotheses capitalize upon this distinction:

$H_{B1_0}$: The random-effects estimator offers a meaningful alternative to the fixed-effects estimator because it is not misspecified.
FIGURE B.1 ASSESSING SPECIFICATION ADEQUACY
HB1: The random-effects estimator does not offer a meaningful alternative to the fixed-effects estimator because it is misspecified.

Hausman (see e.g., Greene 1990b) provides the appropriate test statistic:

\[ H = (\hat{b}_{\text{FEM}} - \hat{b}_{\text{REM}})' \left[ \text{var}(\hat{b}_{\text{FEM}}) - \text{var}(\hat{b}_{\text{REM}}) \right]^{-1} (\hat{b}_{\text{FEM}} - \hat{b}_{\text{REM}}) - \frac{X^2}{k} \]  \hspace{1cm} (B1)

where \( b_{\text{FEM}} \) and \( b_{\text{REM}} \) are, respectively, the parameter estimates from the fixed- and random-effect models.

The third comparison contrasts the 'best' two-way static model to the 'best' one-way static model. These hypotheses are relevant:

HB20: The 'best' two-way panel-data model provides no better insight into donors' charitable-giving impulse than the 'best' one-way model.

HB21: The 'best' two-way panel-data model provides better insight into donors' charitable-giving impulse than the 'best' one-way panel-data model.

The potential comparisons associated with these hypotheses are summarized in Figure B.2.

An F test statistic generated from equation (A12) indicates whether the one-way static fixed-effects model provides better insight into donors' charitable giving than the two-way static fixed-effects model. Comparison of the one- and two-way static random-effects models is facilitated with the following F test statistic:

Appendix B
\[ F = \frac{\text{LM}_{1W} - \text{LM}_{2W}}{\text{LM}_{2W}} - F_{1,2} \]  

(B2)

Detailed in equation (B5) below, \( \text{LM}_{1W} \) is the Lagrange-Multiplier (LM) statistic used to contrast the one-way fixed- and random-effects models. This test statistic tests for the presence of donor-specific components in the error term. Similarly, \( \text{LM}_{2W} \) tests for the presence of donor- and time-specific components in the error term. This test statistic

<table>
<thead>
<tr>
<th>HYPOTHETICAL OUTCOME SETS</th>
<th>APPROPRIATE TEST FOR STATISTICAL COMPARABILITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIRST COMPARISON</td>
<td></td>
</tr>
<tr>
<td>BEST ONE-WAY MODEL</td>
<td></td>
</tr>
<tr>
<td>FIXED-EFFECTS MODEL</td>
<td>F TEST</td>
</tr>
<tr>
<td>FIXED-EFFECTS MODEL</td>
<td>PREDICTIVE PROWESS</td>
</tr>
<tr>
<td>RANDOM-EFFECTS MODEL</td>
<td></td>
</tr>
<tr>
<td>RANDOM-EFFECTS MODEL</td>
<td></td>
</tr>
<tr>
<td>SECOND COMPARISON</td>
<td></td>
</tr>
<tr>
<td>BEST TWO-WAY MODEL</td>
<td></td>
</tr>
<tr>
<td>FIXED-EFFECTS MODEL</td>
<td>F TEST</td>
</tr>
<tr>
<td>RANDOM-EFFECTS MODEL</td>
<td>PREDICTIVE PROWESS</td>
</tr>
<tr>
<td>RANDOM-EFFECTS MODEL</td>
<td></td>
</tr>
<tr>
<td>FIXED-EFFECTS MODEL</td>
<td></td>
</tr>
</tbody>
</table>

(Figure B.2 Identifying the 'Best' Model of Giving)

is detailed in equation (B6) below. Comparison of the one-way fixed-effects and two-way random-effects static models or the one-way random-effects and two-way fixed-effects models is based upon the relative explanatory or predictive prowess of these models. These auxiliary regressions apply:

\[ \ln \text{Contribution}_{it} = \hat{Y}_{PEit} \]  

(B3)

\[ \ln \text{Contribution}_{it} = \hat{Y}_{REit} \]  

(B4)

Appendix B
\( \hat{Y}_{FEit} \) represents the predicted values of either the one- or two-way fixed-effects model. \( \hat{Y}_{REit} \) represents the predicted values of either the one- or two-way random-effects model. If equation (B3) has a higher adjusted R square than equation (B4), the one- or two-way fixed-effects model provides the best insight into donors' giving. Otherwise, the one- or two-way random-effects model provides the best insight.

The final static-model comparison contrasts the cross-sectional or pooled version of the traditional (static) model of giving to the 'best' static panel-data model of giving. These hypotheses facilitate this comparison:

HB3\(_0\): The 'best' static panel-data model provides no better insight into donors' charitable giving than the cross-sectional or pooled version of the traditional model of giving.

HB3\(_1\): The 'best' static panel-data model provides better insight into donors' charitable giving than the cross-sectional or pooled version of the traditional (static) model.

If either the one- or two-way fixed-effects panel-data model produces the 'best' panel-data model, an F test statistic generated from equation (A12) indicates whether the 'best' fixed-effects panel-data model outperforms the pooled or cross-sectional model. If the one-way random-effects model provides the 'best' panel-data model of giving, the following Lagrange-Multiplier (LM) test statistic indicates whether the one-way random-effects model outperforms the pooled model:

Appendix B

168
This Lagrange-Multiplier test statistic shows whether the two-way random-effects model outperforms the pooled model:

\[
L_M = \frac{N T}{2(T - 1)} \left[ \frac{\sum_i \hat{u}_{it}^2}{\hat{u}_{it}} - 1 \right] - \frac{2}{1} \cdot x^2
\]  

\[
L_M = \frac{N T}{2} \left[ \frac{1}{(T - 1)} \left[ \frac{\sum_i \hat{u}_{it}^2}{\hat{u}_{it}} - 1 \right] + \frac{1}{(N - 1)} \left[ \frac{\sum_i \hat{u}_{it}^2}{\hat{u}_{it}} - 1 \right] \right] - \frac{2}{2} \cdot x^2
\]

Except for the absence of a pooled model, the process of selecting the 'best' dynamic and overall models of giving is identical to the one used to identify the 'best' static model. Consequently, further disclosure is unnecessary.

B.2 The 'Best' Model of Giving.⁹⁴

Table B.1 summarizes the specification-adequacy test

---

⁹⁴Because the direction and magnitude of the biases caused by statistical violations cannot be determined, each model is treated as though it is a candidate for specification testing. The dynamic two-way fixed-effects model is shown to have the most desirable specification. This outcome is particularly appealing because the dynamic two-way fixed-effects model has the lowest level of statistical inadequacy and is thus more likely to generate good approximations for parameter estimates.

Appendix B 169
statistics used in identifying the 'best' static model of giving. This identification process begins with a comparison between the static one-way fixed- and random-effects models. With 5 degrees of freedom, the Hausman test statistic of 91.5713, has a P value of 0.0000. This low P value indicates donor-specific effects are correlated with regressors. For this reason, the one-way random-effect model is misspecified and thus unable to provide a reasonable alternative to the fixed-effects model (see HB1_0 and HB1_1). Consequently, the one-way fixed-effects model is retained as the 'best' static one-way panel-data model.

An attempt to impose a similar comparative process upon the static two-way fixed- and random-effects models was thwarted initially by the lack of a positive estimate for the variance component of the time dimension. LIMDEP then attempted to facilitate estimation of the two-way random-effects model by using time-dimension information from the two-way fixed-effects model. Unfortunately, the estimation of the two-way random-effects model still failed because of collinear regressors. For these reasons, the two-way fixed-effects model is retained as the 'best' static two-way panel-data model.

The $F_{7,9662}$ test statistic contrasting the static one- and two-way fixed-effects models, 38.7290, has a P value less than
### TABLE B.1 ANALYSIS OF STATIC MODELS OF GIVING

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>CROSS-SECTIONAL (POOLED MODEL)</th>
<th>PANEL-DATA MODELS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>COEFFICIENT (STD. ERR.)</td>
<td>COEFFICIENT (STD. ERR.)</td>
</tr>
<tr>
<td>CONSTANT</td>
<td>* -3.2961 (0.3562)</td>
<td>* -1.1666 (0.2070)</td>
</tr>
<tr>
<td>LOGINC</td>
<td>0.8710 (0.0385)</td>
<td>* 0.1287 (0.0375)</td>
</tr>
<tr>
<td>LOGPRC</td>
<td>* -0.6057 (0.1111)</td>
<td>* 0.1639 (0.0505)</td>
</tr>
<tr>
<td>MARDUM</td>
<td>0.1956 (0.0576)</td>
<td>* 0.0029 (0.0138)</td>
</tr>
<tr>
<td>AGEDUM</td>
<td>0.7077 (0.0695)</td>
<td>0.7526 (0.0138)</td>
</tr>
<tr>
<td>MUNDEP</td>
<td>** 0.0459 (0.0103)</td>
<td>0.1422 (0.0122)</td>
</tr>
<tr>
<td>ADJ. R SQUARE</td>
<td>0.1663</td>
<td></td>
</tr>
</tbody>
</table>

### STATISTICAL COMPARISON OF STATIC CHARITABLE GIVING MODELS

Pooled vs Two-Way Fixed-Effects. Given df of 138 and 9662, and a F test statistic of 20.5974, P has a value < 0.01. This implies that time- and donor-specific effects have net information content when they are modeled as time- and donor-specific constants. So, the static two-way fixed-effects model is retained as the 'best' static model of giving.

Fixed vs Random. With 5 df, the Hausman test statistic, 96.5713, has a P of 0.0000. This low P value indicates donor-specific effects are correlated with regressors. The random-effects model is rejected and the fixed-effects model is retained.

One-Way Fixed- vs Two-Way Fixed-Effects. With 7 and 9662 degrees of freedom, the F test statistic, 38.7290, has a P value < 0.01. This implies that the incremental information content of time-specific effects exceeds its cost in terms of lost degrees of freedom. So, the two-way fixed-effects model is retained as the 'best' static panel-data model of charitable giving.
0.01. Thus, the incremental information provided by time-specific constants more than offsets it cost in terms of lost degrees of freedom. This empirical evidence leads to the rejection of HB20's null assertion that the 'best' static two-way panel-data model provides no better insight into donors' giving than the 'best' static one-way panel data model. Instead, HB21's alternative assertion is accepted because it claims the 'best' static two-way panel-data model provides better insight into donors' giving than the 'best' static one-way panel-data model.

In contrasting the cross-sectional and two-way fixed-effects models, a highly significant F test statistic of 20.5974 suggests donor- and time-specific effects have net information content. By implication, the pooled or cross-sectional model is rejected and the static two-way fixed-effects is retained for comparison against the 'best' dynamic model of giving (see HB30 and HB31).

The specification-adequacy analysis for the dynamic models of giving is found in Table B.2. Within the context of hypotheses HB10 and HB11, the highly significant Hausman test statistic, 3698.71 (P = 0.0000), supports retention of the one-way fixed-effects model as the 'best' dynamic one-way panel-data model. The two-way fixed-effects model is retained as the 'best' dynamic two-way panel-data model because the

Appendix B
### Table B.2 Analysis of Dynamic Models of Giving

**Panel-Data Models**

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>ONE-WAY FIXED-EFFECTS</th>
<th>ONE-WAY RANDOM-EFFECTS</th>
<th>TWO-WAY FIXED-EFFECTS</th>
<th>TWO-WAY RANDOM-EFFECTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>0.161 (0.012)</td>
<td>-0.880 (0.257)</td>
<td>0.375 (0.593)</td>
<td></td>
</tr>
<tr>
<td>LAGCON</td>
<td>0.216 (0.043)</td>
<td>0.778 (0.006)</td>
<td>0.156 (0.012)</td>
<td></td>
</tr>
<tr>
<td>LAGINC</td>
<td>0.607 (0.101)</td>
<td>-0.997 (0.035)</td>
<td>0.157 (0.042)</td>
<td></td>
</tr>
<tr>
<td>LAGPRC</td>
<td>0.270 (0.042)</td>
<td>0.804 (0.093)</td>
<td>0.354 (0.111)</td>
<td></td>
</tr>
<tr>
<td>LOGINC</td>
<td>0.188 (0.039)</td>
<td>0.188 (0.039)</td>
<td>0.187 (0.044)</td>
<td></td>
</tr>
<tr>
<td>LOGPRC</td>
<td>-1.332 (0.106)</td>
<td>-1.332 (0.106)</td>
<td>-1.181 (0.116)</td>
<td></td>
</tr>
<tr>
<td>MARDUM</td>
<td>0.104 (0.025)</td>
<td>0.104 (0.025)</td>
<td>0.514 (0.059)</td>
<td></td>
</tr>
<tr>
<td>AGEDUM</td>
<td>0.133 (0.031)</td>
<td>0.133 (0.031)</td>
<td>0.015 (0.070)</td>
<td></td>
</tr>
<tr>
<td>MURDEP</td>
<td>0.007 (0.006)</td>
<td>0.007 (0.006)</td>
<td>-0.008 (0.018)</td>
<td></td>
</tr>
<tr>
<td>LEDINC</td>
<td>0.113 (0.034)</td>
<td>0.113 (0.034)</td>
<td><strong>0.073 (0.040)</strong></td>
<td></td>
</tr>
<tr>
<td>LEDPRC</td>
<td>0.204 (0.102)</td>
<td>0.204 (0.102)</td>
<td><strong>0.428 (0.121)</strong></td>
<td></td>
</tr>
<tr>
<td>ADJ. R SQUARE</td>
<td>0.786</td>
<td>0.704</td>
<td>0.787</td>
<td></td>
</tr>
</tbody>
</table>

Fixed vs Random. With 10 df, the Hausman test statistic, 5698.72, has a P of 0.0000. This low P value indicates donor-specific effects are correlated with regressors. Thus, the random-effects model is rejected and the fixed-effects model is retained.

Fixed vs Random. Since there are insufficient degrees of freedom for computing dynamic model coefficients in the time dimension of the random-effects model, the fixed-effects model is retained for comparison against the best one-way model.

---

**Statistical Comparison of Charitable Giving Models**

One-Way Fixed-Effects vs Two-Way Fixed-Effects. With degrees of freedom of 5 and 6895, the F test statistic of 9.6933 has a P value less than 0.01. This low P value implies the incremental information content of the time-specific effects exceed their cost in terms of lost degrees of freedom. Thus, the two-way fixed-effects model is retained as the best dynamic model.
time dimension has insufficient degrees of freedom for computing the coefficients of the two-way random-effects model.\textsuperscript{95}

Given the legitimizing context provided by hypotheses \(H_{2B_0}\) and \(H_{2B_1}\), the \(F_{5,6884}\) test statistic of 9.6933 has a \(P\) value less than 0.01. This low \(P\) value implies that the incremental information content of the time-specific effects exceeds its cost in terms of degrees of freedom. For this reason, the two-way dynamic fixed-effects model is retained as the 'best' dynamic model. Borrowing loosely from the legitimizing context of \(HB_{10}\) and \(HB_{11}\), the final comparison contrasting the static and dynamic two-way fixed-effects models requires an important adjustment. The use of leads and lags in the dynamic model creates a disparity of 2,764 degrees of freedom (1,382 donors * 2 years) between the static and dynamic models. This disparity is eliminated when the static

\textsuperscript{95}In order to obtain parameter estimates for the two-way random-effects model, LIMDEP implicitly computes a weighting factor which takes into account the degree of heterogeneity that exists among the panel's donors (For additional details, refer to summary of Daniel's work appearing in Section 2.3 (page 43), Daniel). One of the steps for accomplishing this task collapses the donor dimension, leaving only the time dimension for computing auxiliary parameter estimates. Because the dynamic model uses leads and lags, only 6 out of the 8 panel years are available for computing these auxiliary coefficients. Because the dynamic models requires estimation of 11 parameters and there are only six observations, the estimation fails for lack of sufficient degrees of freedom.
two-way fixed-effects model is recomputed without the years 1979 and 1986. Given this adjustment, the relevant $F_{5,6895}$ test statistic of 44.5794 has a P value less than 0.01. This evidence supports retention of the dynamic two-way fixed-effects model as the 'best' model of giving. That is, the dynamic two-way fixed-effects model dominates its static and dynamic rivals on specification grounds. Thus, relative to the traditional static model, this year's giving is best understood after taking into account donor- and time-specific effects, donors' habit persistence tendencies, last year's income and price, and next year's income and price.
REFERENCES


References 176


References


References


References


VITA

Kevin Stanton Barrett
August 12, 1991

BUSINESS ADDRESS:
Department of Accounting
Walker College of Business
Appalachian State University
Boone, North Carolina 28608
Tel: (704) 262-6189

HOME ADDRESS:
Rocky Mountain Heights
Route 7, Box 677
Boone, North Carolina 28607
Tel: (704) 265-3218

EDUCATION:
M.B.A., Accounting, Indiana University, Bloomington, 1986.
B.S. (Cum Laude), Accounting, Utah State University, 1982.

HONORS AND AWARDS:
1989 AAA Doctoral Consortium representative.
1989 Southeastern AAA Doctoral Consortium representative.
Phi Kappa Phi (1989).
Beta Gamma Sigma (1986).
Phi Kappa Phi (1982).
Beta Gamma Sigma (1982).
Accounting academic scholarship (1981).

PUBLISHED WORK:


**WORK IN PROGRESS:**


**PRESENTATIONS:**


**DISSERTATION:** *(Defended May 31, 1991)*


**RESEARCH INTERESTS:**

Econometric and experimental economic analysis of tax policy.
WORK EXPERIENCE:

Research Assistant, Virginia Tech; Cherie J. O'Neil & Robert A. Leitch.

Teaching Assistant, Virginia Tech; Principles of Accounting, Survey of Accounting (for non-majors), Intermediate Accounting, Individual Income Tax.

Teaching Assistant, Indiana; Principles of Accounting.


Staff Accountant, Davis and Bott CPAs, 1981.

PROFESSIONAL CERTIFICATIONS:

Certified Internal Auditor, 1986.

Certified Public Accountant, 1982.

Certified Management Accountant, 1982.

TEACHING INTERESTS:

Taxation, Intermediate Accounting, Principles of Accounting, Governmental & Nonprofit Accounting, Advanced Accounting.