2013

# Strategic Responses to Tax and Transfer Policy: Welfare Competition, Tax Competition and the Elasticity of Taxable Income

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STRATEGIC RESPONSES TO TAX AND TRANSFER POLICIY:
WELFARE COMPETITION, TAX COMPETITION, AND THE ELASTICITY OF TAXABLE INCOME

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DISSERTATION

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A dissertation submitted in partial fulfillment of the
Requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By
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2013

ABSTRACT OF DISSERTATION

STRATEGIC RESPONCES TO TAX AND TRANSFER POLICY: WELFARE COMPETITION, TAX COMPETITION, AND THE ELASTICITY OF TAXABLE INCOME

My dissertation consists of three essays focused on identifying the strategic responses of governments and individuals following changes in the tax and transfer system. Two essays contribute to the literature on fiscal competition, focusing on state level polices aimed at redistributing income. A third essay contributes to the literature estimating the responsiveness of individual's incomes to changing marginal tax rates. A better understanding of these responses contributes to our ability to design an optimal tax and transfer system in a federalist nation.

In essay 1 I employ a spatial dynamic approach to investigate interstate welfare competition across multiple policy instruments and across three distinct welfare periods - the AFDC regime, the experimental waiver period leading up to the reform, and the TANF era. Results suggest the strategic setting of welfare policy occurs over multiple dimensions of welfare including the effective benefit level and the effective tax rate applied to recipient's earned income. Furthermore, strategic behavior appears to have increased over time, a finding consistent with a race to the bottom after welfare reform.

Another form of interstate competition examined in Essay 3 is the spatial patterns in state level estate tax policy. My examination follows a major reform which greatly altered both the state and federal estate tax landscape. This study develops a model in which a state's tax base and rate are simultaneously determined. Results indicate a state's estate tax base is negatively influenced by its own tax rate and positively influenced by the tax rate set in neighboring jurisdictions. A state's own tax rate is also found to be positively influenced by the tax rates set in neighboring jurisdictions.

Last, Essay 2 uses matched panels from the Current Population Survey for survey years 1980-2009 to estimate the elasticity of taxable income (ETI) and how it varies in response to measurement of the tax rate, heterogeneity across education attainment, selection on observables and unobservable, and identification.  Substantial variation in the ETI across all key economic and statistical decisions is found.

KEYWORDS: Welfare Competition, Tax Competition, Income Taxation, Taxable Income, Estate Tax

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In loving memory of my father, Patrick James Burns, and for my mother Suzanne, and my sisters, Emily and Hannah, who have been constant sources of support throughout the dissertation process.

ACKNOWLEDGEMENTS

Throughout my doctoral studies and dissertation research in the Department of Economics at the University of Kentucky, I have benefited greatly from guidance and investments several individuals. First, I thank Professor James Ziliak for all the time and knowledge he invested in me as well as his much needed patience and encouragement. The opportunity to work under his direction at the Center for Poverty Research provided an extremely valuable learning experience which has helped shape me as a researcher. Next, I thank Professors William Hoyt, David Wildasin, and Scott Hankins for agreeing to serve on my dissertation committee and for the roles they played in my education, both in the classroom and by proving invaluable feedback and encouragement throughout the dissertation process. I would also like to thank G. Rod Erfani and Alan Bartley who first sparked my interest in Economics during my undergraduate studies at Transylvania University and encouraged me to pursue these interests. Finally I thank my mother, Suzanne Burns, and my sisters, Emily and Hannah Burns, for their love and support throughout my graduate studies.

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# 1 Introduction

Understanding how economic agents react to changes in the tax and transfer system has long been a topic of great interest to both policy makers and academics. Moreover, given today's fiscal climate, in which further income tax hikes and cuts to social safety net programs loom in the near future, an enhanced knowledge of such responses will be all the more important. Economists working at the intersection of public and labor economics have devoted much research into identifying behavioral elasticities such as the compensated elasticity of labor supply with respect to marginal tax rates and more recently, the elasticity of taxable income. Because elasticities such as these will be inversely related to both the optimal size and progressively of the public sector, pinning them down is crucial for deriving important tax parameters such as the revenue-maximizing rate of taxation for high earners.

Another set of important questions studied by those interested in the design and reform of our tax and transfer system pertain to matters of fiscal federalism, a subfield of public economics addressing questions related to how to delegate policies among different levels of government. Such questions have been particularly relevant with regards to the nations transfer system given the 1996 welfare reform created by the PRWORA legislation which further decentralized welfare authority to the state governments and the ongoing discussions of how to reform larger programs such as the Supplemental Nutrition Assistance Program (SNAP) and Medicaid. The literature on fiscal competition, which studies how decentralized governments respond to policies set in competing jurisdictions (horizontal competition) or higher levels of government (vertical competition) has been key to understanding the economic implications of such choices. For instance, the literature has demonstrated how inter-state competition over mobile individuals and capital can theoretically lead to a situation sometimes referred to as a 'race to the bottom,' in which jurisdictions compete with each other to offer the most attractive fiscal climate and in doing so reach an equilibrium in which taxes (or the generosity of transfer programs) are lower than they would have been under a centralized system. By examining the behavior of states governments sorrounding past reforms, we can learn much about the strength of inter-state competition and its implications for future policy.

To enhance the body of knowledge relating to the matters discussed above, this dissertation consists of three essays that focus on identifying the strategic responses of both state level governments and individuals following changes in the tax and transfer system.Two essays contribute to the literature on fiscal competition. Both of which focus on state level polices aimed at redistributing income. A third essay contributes to the literature estimating the responsiveness of individual's incomes to changing marginal tax rates. As discussed above, a better understanding of these responses contributes to our ability to design an optimal tax and transfer system in a federalist nation. In essay 1 I use a spatial dynamic approach to investigate interstate welfare competition across multiple policy instruments and across three distinct welfare periods - the AFDC regime, the experimental waiver period leading up to the reform, and the TANF era. Results suggest the strategic setting of welfare policy occurs over multiple dimensions of welfare including the effective benefit level and the effective tax rate applied to recipient's earned income. Furthermore, strategic behavior appears to have increased over time consistent with a race to the bottom after welfare reform. Another form of interstate competition is examined in Essay 3 which investigates spatial patterns in state level estate tax policy following a major reform which greatly altered both the state and federal estate tax landscape. This study develops a model in which a state's tax base and rate are simultaneously determined. Results indicate a state's estate tax base is negatively influenced by its own tax rate and positively influenced by the tax rate set in neighboring jurisdictions. A state's own tax rate is also found to be positively influenced by the tax rates set in neighboring jurisdictions. Last, Essay 2 uses matched panels from the Current Population Survey for survey years 1980-2009 to estimate the elasticity of taxable income (ETI) and how it varies in response to measurement of the tax rate, heterogeneity across education attainment, selection on observables and unobservable, and identification.

Substantial variation in the ETI across all key economic and statistical decisions is found.

## 2 Was there a 'Race to the Bottom' After Welfare Reform?

### 2.1 Introduction

The 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) abolished the federal entitlement program Aid to Families with Dependent Children (AFDC) and replaced it with Temporary Assistance to Needy Families (TANF), a state administered block-grant program. In doing so, the federal government granted states much greater latitude in the design of their respective welfare programs. Leading up to the passage of the reform there was much speculation and debate over the possibility that states would use their new found freedom to "race to the bottom" in setting welfare generosity. Canonical models of fiscal federalism have long suggested that income redistribution, specifically in the form of assistance to the poor, should fall into the realm of responsibility of the federal government (Stigler (1957), Musgrave (1959), Oates (1972)).[1] With welfare, it has been argued that decentralized benefit-setting could trigger competition among the states. In such a scenario, policy makers fear that they may attract poor populations from neighboring states, or become a 'welfare magnet,' if relatively generous benefits are offered. To avoid this outcome, states may strategically reduce the generosity of their welfare programs and compete with neighbors to offer less desirable benefits.

To gauge the likelihood of this scenario, researchers began looking for evidence of competitive behavior among states before the reform went into effect (Brueckner (2000), Figlio *et al.* (1999), Shroder (1995), Rom *et al.* (1998), Saavedra (2000a)).[2] However, little is actually known about the extent of strategic competition after welfare reform. In effect, the question 'did welfare reform actually kick off a race to the bottom?' remains unanswered. Understanding state behavior following the reform is especially relevant today

[1] While the mobility of individuals generally leads one to view local governments as constrained in the amount of redistribution they can carry out, this normative position has not gone unchallenged. Under certain assumptions, some have shown local redistribution to be efficient (Pauly (1973), Epple and Romer (1991)).

[2] The focus of these studies was the AFDC statutory maximum benefit level which was determined at the state level.

given growing political pressures to further reform the social safety net and specifically the current proposals that would block grant funding and give states more control over additional programs including medicaid and the Supplemental Nutritional Assistance Program (SNAP). Using dynamic spatial econometric methods, this paper provides the first evidence on competition after the 1996 reform.

Because of the large array of new policies available to state policy makers (time limits, family caps, sanctions, earnings disregards, etc.), a test of welfare competition that simply extended past methodologies over the TANF era would miss many dimensions over which states could conceivably compete. While the statutory benefit level remains a policy instrument readily available for reform, the water is muddied by the numerous other instruments states now have at their disposal.[3] If states have in fact engaged in a "race to the bottom", it is entirely possible that they did so through more restrictive access, greater policy stringency, or some combination of these and other factors. I extend the literature by utilizing micro caseload data to construct a unique panel of state level welfare policy variables. These include the effective benefit level, the effective tax rate on recipients earned income, state sanction use, and ease of access to benefits. Taken together these variables more fully encompass a state's welfare policy bundle and the channels through which they might compete.

A second contribution of the analysis aims to more fully understand the evolution of competitive behavior surrounding the reform. Though the PWRORA legislation marked the official transition from AFDC to TANF, implementation was not instantaneous. The two regimes were separated by an experimental period of 'laboratory federalism.'[4] The

[3]A policy instrument that states do not have at their disposal is the use of any kind of residency requirement. The use of such policies has been ruled unconstitutional by the Supreme Court - once under the AFDC regime (Shapiro v. Thompson (1969) and again following PWRORA after fifteen states attempted to implement policies which would pay lower benefits to newcomers (Saenz v. Roe (1999).

[4]A provision of the Social Security Act, dating back to 1962, permitted the secretary of Health and Human Services to waive the rules and regulations surrounding AFDC in certain contexts. Specifically, states had the power to petition the U.S. Department of Health and Human Services for such waivers allowing them to implement experimental programs or policies designed to increase program effectiveness(Grogger and Karoly (2005)).

existence of such a period provides a unique opportunity for investigating changes in intensity of strategic behavior. Specifically, during the experimental "waiver period," states had additional policy freedoms but were not yet bound by the new TANF provisions and financing arrangements. To exploit the changing policy landscape, I analyze strategic policy setting over a twenty-five year window (1983-2008) divided into three distinct periods: the AFDC era (1983-1991); the experimental waiver period (1992-1996); and the post reform TANF regime (1997-2008). Through this division I can test for changes in the intensity of strategic behavior across the different regimes.

Finally, though the importance of dynamics has been recognized in the welfare caseload literature (Ziliak *et al.* (2000), Haider and Klerman (2005)), the welfare competition literature has largely ignored the importance of dynamics in the determination of welfare policy. To address this matter, I further extend the literature by providing the first dynamic estimates of welfare competition. To do so, I adopt a spatial dynamic panel estimator which permits both short and long run estimates of strategic policy setting. The dynamic specification can be rationalized on several grounds. First, there are likely to be lags in the diffusion of information about changes in neighbors' welfare policy. Second, the political process takes time. States wishing to enact policy changes in response to their neighbors' policies may not be able to do so immediately. Third, state welfare policies are highly persistent (Ziliak *et al.* (2000), Haider and Klerman (2005)) and failing to control for last years policies, or state dependence, may lead one to overstate the magnitude of strategic behavior. Through the addition of dynamics, one is provided a better understanding of the importance played by strategic behavior in the determination of state policy over time.

The static model shows that states strategically set welfare policies in conjunction with those of their neighbors. Moreover, this strategic behavior was not limited to the statutory benefit level examined by the past literature. Rather, it spanned multiple policy instruments affecting the effective benefits level and tax rates faced by recipients in each state, consistent with competition over the benefit base. Furthermore, it appears strategic behavior intensified in the waiver and TANF periods. For instance, during the AFDC regime, estimates suggest states responded to a 10 percent cut in the effective benefit level of their neighbors' with an own cut of around eight and one half percent. This magnitude increased to nine percent and then nine and a third percent for the waiver and TANF periods, respectively. When the models are augmented to allow for asymmetrical policy responses (i.e. states' responses are conditioned on their relative position to their neighbors), I find that states offering relatively generous policies are more responsive to cuts in generosity by bordering states as one would expect in a "race to the bottom" scenario (Figlio *et al.* (1999)). Furthermore, the three period analysis reveals that the asymmetrical response behavior is concentrated in the waiver and TANF regimes.

Finally, the results demonstrate the importance of modeling welfare competition in a dynamic framework. In terms of importance, lagged own state policy variables clearly dominate those of neighbors for short run policy determination. Spatial coefficients, which capture a state's reaction to its neighbor's policies, are reduced in economic importance and in some instances lose statistical significance under the dynamic specification. Most notable is the case of the maximum benefit level. Once controlling for a states' lagged own maximum benefit level, the maximum benefit level of bordering states no longer appears to exert much influence on state policy choice. However, evidence of strategic policy setting in both the short and long run remains for many of the new variables under consideration, especially the effective benefit level and the effective tax rate on earned income. Long run coefficients suggest that neighbor policy does play an important role in a state's determination of welfare policy over time. Sensitivity analysis reveals findings are robust to multiple spatial weighting schemes and specification choices.

### 2.2 Welfare Reform and the "Race to the Bottom"

The PRWORA legislation, now commonly referred to as welfare reform, sought to "end welfare as we know it." As outlined in Blank (2002), the major reform provisions included the devolution of greater policy authority to the states, the change in financing, ongoing work requirements, incentives to reduce non-marital births, and a five year maximum time-limit. Of these provisions, the first and second were central to the "race to the bottom" debate.

### 2.2.1 Greater Policy Authority for the States

Under TANF, states were given increased discretion over eligibility, the form and level of benefits, and the ability to impose even more stringent time limits and work requirements if they so chose (Blank (2002), Grogger and Karoly (2005)). While many of the new policies were designed to force participants to work and punish or sanction those who did not comply, others were implemented to increase the reward to working. Examples of the latter included reduced statutory tax rates on recipient's income as well as expansions in earnings disregards and liquid asset limits which determined benefit levels and eligibility (Ziliak (2007)). These so called "carrots and sticks" of welfare reform were applied at the discretion of each state and entered into use during the early 1990s in the experimental waiver period.

Waiver-based reforms that had gone largely unused until the 1990s suddenly became a key mechanism in the states' push for reform. During this time, eighty-three waivers were granted to forty-three states and the District of Columbia (Grogger and Karoly (2005)).[5] For example, sixteen states were granted approval to implement various statewide time-limit policies. Of these, Iowa was the first state to receive approval in 1993. Other midwestern states to adopt time-limit waivers included Indiana (1994), Nebraska and Illinois (1995) and Ohio (1996). Connecticut implemented the strictest time-limit policy of twenty-one months which applied to the whole family. Delaware, Virginia, and South Carolina also received approval for strict full family time-limits of twenty-four months. Statewide family-cap waivers were granted to nineteen states between 1992-1996. The majority of these

[5] The following information on specific state waiver policies is drawn from Chapter 2 of Grogger and Karoly (2005).

allowed no increase in benefits for additional children beyond a certain number. Statewide financial-incentive waivers were granted in twenty states over the same period. Before the waiver period, welfare recipients faced a benefit reduction ratio of 100 percent after just four months of working.[6] In an attempt to encourage labor force participation or "make work pay," states experimented with increasing the income disregard and lowering the implicit tax rate. Michigan, for instance, allowed a $200 disregard and lowered the tax rate on earned income to twenty percent while Connecticut allowed recipients to keep 100 percent of their earnings up until the federal poverty line. These constitute just a few of the examples of policies states initially enacted during the waiver period and carried over to TANF. Perhaps unsurprisingly given the evolution of U.S. welfare reform, it was not only these new waivers state policymakers pushed for in the final national reform. They also sought the devolution of responsibility in program design from the federal level to the state.

Naturally, some believed this new found flexibility in welfare design would prove efficiency enhancing, as states could now tailor their programs to meet their citizens' (both tax-payers and potential recipients) wants and needs more closely. Others, however, were concerned that the further decentralization of benefits would have a more worrisome effect – the aggravation of interjurisdictional externalities suggested by the fiscal federalism tradition. While popular usage of the term "race to the bottom" tends to overstate the situation or connote "a draconian tendency to slash welfare benefits to the bare minimum, mimicking the outcome of the least generous state," the fact remains that economic theory does point to a downward bias in generosity (Brueckner (2000)). This benefit underprovision result has been demonstrated in the literature many times. The standard models of benefit competition, built on the work of Brown and Oates (1987), Bucovetsky (1991), and Wildasin (1991) consist of multiple jurisdictions composed of taxpayers and mobile poor non-taxpayers who receive a welfare benefit. The welfare benefit is selected in each jurisdiction to maximize the utility of the taxpayers (who care about the poor in their own ju-

[6] AFDC's first finical work incentive, known as the "thirty-and-a third" policy, was enacted in 1967 but later eliminated in 1981 for recipients with four months of work.

risdiction) taking into account the benefit level in other jurisdictions. First order conditions from these models take on the form of a Samuelson condition for the optimal provision of a public good where the sum of the taxpayers marginal utility gain from increasing the benefit is equal to the marginal cost. The suboptimality of this result is easily demonstrated by obtaining the same condition for the case in which the poor are immobile. Comparison reveals that the marginal cost of raising benefits will be higher when the poor can migrate which leads to a lower benefit level than in the no migration case. Thus decentralized benefit setting is said to lead to benefit under-provision.

To test this prediction, the past welfare competition literature focused on the maximum AFDC benefit guarantee (sometimes augmented to include food stamps) for a given family size. However, this statutory maximum may not sufficiently reflect a state's welfare policy. Under welfare reform, other critical factors include the rates at which states 'claw back' benefits as a recipient's income increases along with the levels and sources of income that may be excluded from benefit determination formula (Ziliak (2007)). These factors which are determined by state policy act to drive a wedge between the statutory maximum benefit level and the prevailing average effective benefit. This can be demonstrated with the standard benefit determination formula denoted as: $B = MB - brr * (WH + N - D)$, where MB is the maximum benefit guarantee, brr is the states benefit reduction ratio (which was set at 100 percent under AFDC), WH is labor income, N is any non-labor income, and D is the earnings disregard). Prior to the reform many states did implemented earnings disregards which led to effective tax rates of less than 100 percent. However, they were bound by the statutory benefit reduction rate of 100 percent. During the waiver period and following TANF, many states set new benefit reduction rates and earning disregard policies. For instance, Michigan and Maryland implemented a benefit reduction rate of only twenty percent during the waiver period while rates of twenty-five percent, thirty-three percent, and fifty percent were set in place by Vermont, California, and New Hampshire, respectively.

Figure 2.1 illustrates the impact of such policies by plotting the time series trend for the average statutory maximum and average effective benefit level for a family of three.[7] For both variables a clear downward trend emerges in the late 1980s, which is consistent with welfare competition. Even more interesting is the divergence between effective and statutory benefit guarantees whose onset coincides with the 1996 reform. Ziliak (2007) notes that the falling effective guarantees make welfare less attractive and are in line with the reform goals of encouraging work and discouraging welfare use. One could also speculate that these falling effective guarantees are consistent with states' strategic efforts to keep their welfare programs from appearing to be more desirable than their neighbors. Though the effective benefit level may better reflect a state's generosity relative to the statutory maximum, the picture is not complete until one considers the effective tax rates faced by recipients. The effective tax rate on earned income reflects the rate at which a state reduces the monthly benefit amount paid to recipients as they earn labor income. State policies such as reduced statutory rates and earnings disregards, lower the effective rate of taxation and thus increase both the level of generosity and work incentives. Before the reform, this tax rate had a statutory value of 100 percent though in practice it was much lower and displayed a considerable degree of cross-state heterogeneity (Lurie (1974), Hutchens (1978), Franker *et al.* (1985), McKinnish (2007a)). After the reform, the rates fell rapidly as seen in Figure 2.2 A strong case can be made for the use of these 'effective' variables. Though they cannot separately identify the individual policies, these variables will reflect a states' collective use of policies such as family caps, asset limits, partial sanctions and earning disregards, as well as caseworker discretion in the application of these policies (Ziliak (2007)).

However, there is also an extensive margin of generosity to consider. States can set strict eligibility criteria, harsh sanction policies, or shorter more restrictive time limits. Three additional measures therefore aim to capture aspects of state policy not represented by the benefit and tax rate instruments discussed above. The first is the approval rate which is meant to proxy for ease of access to welfare benefits. The latter two reflect a state's strin-

[7] The effective benefit variable is constructed using administrative micro caseload data from the AFDC Quality Control System and the National TANF Data System. See data section for further detail.

gency in terminating cases through the use of sanction and other non-sanction state polices (such as shortened time limits). These measures are constructed using micro caseload data available only for the post-reform regime. Figure 2.3 illustrates a national trend towards declining case approval rates coinciding with an increasing trend in case termination due to sanctions. Specifically, average state case approvals fell approximately seventeen percent between 2000 and 2008 while sanction use nearly doubled. Overall, the trends documented here suggest a tendency towards reducing welfare generosity along multiple margins consistent with a race to the bottom. Detailed information on the construction of all variables and their sources are provided in the data section.

The additional policy autonomy for the states was not the only factor cited in the growing debate on whether states would "race to the bottom." Critics of the reform also argued that the new cost-sharing arrangement between states and the federal government would exert further downward pressure on benefits.

### 2.2.2 Change in Federal Cost Sharing

Brueckner (2000) demonstrated that a price correction mechanism, such as a system of matching grants with the federal government, can be used to decrease the price of additional welfare spending and restore benefits to their optimal level. Such a system was in existence prior to PRWORA. The reform, however, replaced this cost-sharing scheme with a block grant system. With the old system of open-ended matching grants, states would share any increase in their costs with the federal government (sometimes with the federal government footing as much as eighty percent of the bill).[8] Under TANF, states receive a lump sum block grant which was initially tied to the level of federal matching-grant payments a state received in 1994 (Brueckner (2000)).[9] As noted in Rom *et al.* (1998), each

[8] Under AFDC, the federal matching rate for each state was calculated based on the state's per capita personal income (PCI). The specific formula, match rate= $100 - .45 * \frac{(StatePCI)^2}{U.S.PCI}$, was the same formula used to determined the Medicaid matching rate and was designed to give relatively poorer states more federal assistance.

[9] The amount of the block grants was not tied to inflation. Between 1997 and 2011, the value of these grants has been eroded by nearly thirty percent

state therefore bears the full marginal cost of any increased spending in its welfare program. Alternatively, states gain the full marginal benefit of any cost savings they incur. In such a setting, attracting welfare migrants from low-benefit states would be quite costly, and more so than before. Consequently, it was suggested that welfare competition could intensify post reform, speeding up the race to the bottom (or at least the race to the benefit floor required by federal law). Policy makers, perhaps in anticipation of strong downward pressure on benefits levels, set "maintenance of effort" requirements stipulating that states may not spend less than eighty percent of what they spent in 1994 (or seventy-five percent if they meet minimum work requirements).[10]

While theory suggests the move towards greater state policy authority and block grant financing could have led states to underprovide or even "race to the bottom" in setting their welfare generosity, assessing the importance of any resulting competitive behavior is an empirical matter.

#### 2.2.3 Empirical Tests of "Race to the Bottom"

Because welfare migration is held to be the key mechanism in race to the bottom theory, initial empirical studies sought to test whether or not migration actually occurred at any meaningful magnitude. However, these studies found rather mixed results.[11] The lack of conclusive results confirming welfare migration does not prima facie rule out race to the bottom behavior. As explained by Brueckner (2000), if state governments merely perceive generous welfare benefits to attract welfare migrants, then the requirements for strategic interaction and the resulting race to the bottom are met. He therefore argues, "because it focuses directly on the behavioral response that leads to a race to the bottom, which may arise even if welfare migration is mostly imaginary, a test for strategic interaction may be more useful than a test for migration itself."

[10] Like the block grants, MOE requirements were not indexed for inflation and have thus greatly declined.

[11] See Brueckner (2000) for a survey covering empirical studies of welfare migration. More recent works finding evidence of moderate welfare migration include McKinnish (2004, 2007), and Gelbach (2004).

The canonical approach is to employ a fiscal reaction function that relates the welfare benefit level in one state to the benefit level in surrounding states, conditional on a state's socioeconomic conditions (the poverty rate, female unemployment rate, state per capita personal income, population, governor's political party, etc.). Equation (1) represents the typical model,

$$b_i = \phi \sum_{j \neq i} \omega_{ij} b_j + X_i \beta + \varepsilon_i \tag{1}$$

Here $b_i$ represents the benefit level in state i, while $b_j$ is the benefit level in all other states j, where $j \neq i$. $X_i$ is a matrix of controls for state i, $\beta$, its accompanying coefficient vector, and $\varepsilon_i$ is an error term. The weights, or importance, state i attaches to the benefit levels in other states make up the $\omega_{ij}$ vector. Lastly, $\phi$ is the parameter representing the slope of the reaction function. This parameter will take a non-zero value in the presence of strategic interaction.[12]

To estimate equation (1) an a priori set of weights that determines the pattern of interaction between state i and their neighbor's must be specified. Consequently, the question as to which states should be considered neighbors is an important one. In related literatures investigating strategic tax and expenditure policy setting, "economic" neighbors (which are not necessarily geographic neighbors) have been defined based criteria such as racial composition or income (Case *et al.* (1993)). However, because welfare migration (or the fear of welfare migration) is the main factor behind strategic interaction, it is natural to assume a state will be most concerned with the policies of their geographic neighbors - arguably more so, than in related literatures when strategic interaction is driven by capital mobility.[13] Therefore, my initial weight matrix, WI, is a simple contiguity matrix where each state assigns a weight of zero to noncontiguous states ($\omega_{ij} = 0$) and equal weights ($\omega_{ij} = 1/n_i$)

[12] Strategic interactions can be explained by behaviors such as welfare competition, yardstick competition, or policy copycatting among states.

[13] Saavedra (2000) argued that a state will be more fearful of attracting welfare migrants from nearby states due to both information issues and the fact that migration costs grow with distance.

to bordering states where $n_i$ is the number of states contiguous to i. Because one's geographic neighbors remain unchanged, the weights for each state will be time invariant. All baseline models are estimated with this simple weighting scheme. Weighting schemes in which a state scales the importance they attribute to neighbors based on population flows and distance are explored in the sensitivity analysis and discussed therein.

Because benefit levels in different states are believed to be jointly determined, the inclusion of benefit levels on the right side of equation (1) creates an endogeneity problem that must be addressed in estimation. Common methods include reduced form estimation using Maximum Likelihood (ML) spatial econometric techniques and an instrumental variable approach. Past studies of AFDC benefit competition employing the reduced form approach include Saavedra (2000) and Rom et. al (1998).[14] Both author's estimate versions of what has become known in the literature as the spatial lag model with some key distinctions. Specifically, Saavedra's model is adopted to allow errors to follow a spatially autocorrelated process and is applied to several cross sections (1985, 1990, and 1995). Rom *et al.* (1998) use a panel of data covering 1976-1994. They include a temporal lag of AFDC benefits among their control variables in order to address contemporaneously correlated errors but do not take into account spatial error correlation.[15] In both studies, estimates of $\phi$, the slope of the reaction function are positive and statistically significant. One drawback with this type of econometric approach is the need to impose restrictions on the reaction function's slope parameter.[16] Another is the fact the ML spatial methods require the inversion of the spatial weight matrix which can be computationally demanding (Kukenova and Monteiro (2009), Kelejian and Prucha (1998), Lee (2007)).

[14]This method requires inverting the model given by (1). Specifically, one takes the matrix form of (1) given by $B = \phi WB + X\beta + \epsilon$ and solves for B which yields the reduced form equation $B = (I - \phi W)^{-1}X\beta + (I - \phi W)^{-1}\varepsilon$. The equation can then be estimated using ML techniques assuming $(I - \phi W)$ is invertable.

[15]Under the reduced form approach, failing to account for spatial error correlation can result in spurious evidence of welfare competition. The inclusion of the lagged dependent variable introduces further econometric issues which are not addressed in Rom *et al.* (1998) but are in the current paper.

[16]Consistent and efficient estimation of model parameters with MLE requires the structure of the interaction given by the product of $\phi$ and W in the reduced form model to be nonexplosive. In the usual case, $\phi$ must be less than one in absolute value.

Figlio *et al.* (1999) use a two-stage IV approach to investigate the extent of strategic interaction present among states over the period 1983 to 1994.[17] Neighbor's benefits are instrumented with the weighted average of a subset of neighbor covariates, a common approach in the literature. Substantial evidence in favor of strategic benefit setting is found. Evidence of asymmetric responses to changes in neighbors benefits levels are also found. Specifically, states appear to respond much stronger when neighbors cut benefits and less so when they increase them. Evidence of benefit competition has not been limited to the U.S.. Using similar methodologies Dahlberg and Edmark (2008) and Fiva and Rattsø (2006) find evidence consistent with a race to the bottom in Swedish and Norwegian municipalities respectively. See Figure 2.4 for details regarding the weighting schemes, data choice, estimation technique and findings for these past benefit competition studies. In addition to the studies included in Figure 2.4, Shroder (1995), Berry *et al.* (2003), and Bailey and Rom (2004) also addressed the question of interstate welfare competition using somewhat different econometric approaches. Of these studies, Bailey and Rom (2004) is the only to produce strong evidence of strategic welfare competition.

## 2.3 Estimation Issues

As previously discussed, the welfare competition literature has largely ignored the importance of dynamics in the determination of welfare policy. In part, this is likely due to the fact that spatial estimators capable of providing proper econometric treatment to both an endogenous spatial term and a lagged dependent variable have only recently become available. Also, some of the initial tests for welfare competition which sought to sign the slope of the theoretically ambiguous reaction functions were preformed with cross sectional data. However, because a states welfare policies are likely as much a function of time as they are of space, a dynamic framework is required to identify the importance of strategic interac-

[17] While two-stage IV methods may be inefficient relative to ML methods, they have the advantage of being computationally simpler and avoid strong assumptions on the normality of the error term (Lee (2007)). Also IV produces results which are robust to the presence of spatial error correlation.

tion in the determination of state welfare policies.

This analysis implements a dynamic estimator new to the welfare competition literature. Specifically, I use the generalized method of moments (GMM) estimator proposed by Blundell and Bond (1998) that has become increasingly popular in the empirical literature dealing with spatial dynamic panel models with several endogenous variables.[18] I begin with a basic empirical model of strategic interaction similar to those previously discussed augmented to include a lagged dependent variable.

$$Y_{it} = \gamma Y_{it-1} + \phi \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt} + X_{it}\beta + \alpha_i + \delta_t + \varepsilon_{it} \qquad (2)$$

Here $Y_{it}$ represents each of the six welfare policy instruments under investigation for state i in time t. $Y_{jt}$ represents these policies in all other states j at time t, where $j \neq i$. State fixed effects, time effects, and the i.i.d error term are denoted by $\alpha_i$, $\delta_t$, and $\varepsilon_{it}$ respectively. The importance or weight assigned to state j by state i at time t $(j \neq i)$ is represented by $\omega_{ijt}$.

Note that the static model given by equation (1) is embedded within this equation when $\gamma = 0$, or a state's lagged policies are not included in the model. With the dynamic model given by (2), one can obtain estimates of strategic policy setting for both the short and long run. The estimate of strategic policy setting over the short run is given by the coefficient, $\phi$, while the long run coefficient is calculated using the short-run coefficient and the coefficient on the lagged dependent variable. Specifically, the long run coefficient is equal to $\frac{\phi}{1-\gamma}$.[19] Estimates of the short run coefficient, $\phi$, capture the magnitude of a state's immediate policy reaction to those of its neighbors while long run coefficients capture the policy adjustment process. Consequently, differences between the short and long run estimates

[18] Kukenove and Monteiro (2009) and Jabobs et al. (2009) both consider the extension of the Blundell Bond (1998) estimator for the estimation of models with spatially lagged dependent variables. Monte Carlo simulations show the estimator performs well in terms of bias and RMSE and that the system GMM estimator outperforms the Arrelano and Bond difference estimator. Papers applying the System GMM estimator to spatial panels include Madariaga and Poncet (2007), Foucault *et al.* (2008), Wren and Jones (2011), Bartolini and Santolini (2011), and Neumayer and de Soysa (2011).

[19] Standard error for the long run coefficient are obtained using Stata's nlcom command. Calculations are based on the delta method.

will be governed by the degree of policy persistence given by the parameter $\gamma$.

In order to remove the fixed effects ($\alpha_i$) which are correlated with the covariates and the lagged dependent variable, equation (3) is first differenced and rewritten as:

$$\Delta Y_{it} = \gamma \Delta Y_{it-1} + \phi \Delta \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt} + \Delta X_{it} \beta + \Delta \delta_t + \Delta \varepsilon_{it} \tag{3}$$

Though the data transformation removes the fixed effects, the lagged dependent variable remains endogenous since the term $Y_{i,t-1}$ included in $\Delta Y_{it-1} = Y_{i,t-1} - Y_{i,t-2}$ is correlated with the $\varepsilon_{i,t-1}$ in $\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$. So too does the neighbor's jointly determined policy. Finally, any predetermined covariates in X become potentially endogenous given that they too may correlate with $\varepsilon_{i,t-1}$. Following the GMM procedure, one can instrument endogenous regressors with deeper lags which remain orthogonal to the error. Under the assumption that error term is not serially correlated, valid moment conditions for the endogenous variables are given by conditions (4)-(6)

$$E[Y_{i,t-\tau} \Delta \varepsilon_{it}] = 0;\ for\ t = 3, ...T\ and\ 2 \leq \tau \leq t-1 \tag{4}$$

$$E[W_{i,t-\tau} Y_{i,t-\tau} \Delta \varepsilon_{it}] = 0;\ for\ t = 3, ...T\ and\ 2 \leq \tau \leq t-1 \tag{5}$$

$$E[X_{i,t-\tau} \Delta \varepsilon_{it}] = 0;\ for\ t = 3, ...T\ and\ 1 \leq \tau \leq t-1 \tag{6}$$

Conditions (4) and (5) restrict the set of instruments for the change in own lagged policy, $\Delta Y_{i,t-1}$, and the change in neighbor's policy, $\Delta \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt}$, to levels of their second lags or earlier. Condition (6) requires predetermined covariates be instruments with their first lags or earlier. Because lagged levels of variables can be weak instruments when a variable is highly persistent (as is the case with the welfare variables), the system estimator of Blundell and Bond (1998) adds the original levels equation given by (2) to the model with the additional moment conditions:

$$E[\Delta Y_{i,t-\tau}\varepsilon_{it}] = 0;\ for\ t = 3, ...T \tag{7}$$

$$E[\Delta W_{i,t-\tau}Y_{i,t-\tau}\varepsilon_{it}] = 0;\ for\ t = 3, ...T \tag{8}$$

$$E[\Delta X_{i,t-\tau}\varepsilon_{it}] = 0;\ for\ t = 2, ...T \tag{9}$$

The regression in levels given by equation (2) and the regression in differences given by (3) are combined into a system and estimated simultaneously with lagged levels serving as instruments for the difference equation and lagged differences serving as instruments for the levels equation in accordance with the moment conditions (4)-(9). The model is estimated in natural logs allowing coefficients to be interpreted as elasticities.

The consistency of the GMM estimator will depend of on the validity of the instruments. However, under the above moment conditions, the instrument count grows prolifically in T creating problems in finite samples (Ziliak (1997)).[20] To avoid these problems I follow Kukenova and Monteiro (2009) and Jacobs *et al.* (2009) and collapse the instruments.[21] Collapsed moment conditions differ from the those proposed in Arellano and Bond (1991) where each moment applies to all available periods rather than a particular time period. For instance, under this modification the moment condition given by (4) now appears as

$$E[Y_{i,t-\tau}\Delta\varepsilon_{it}] = 0;\ 2 \leq \tau \leq t-1 \tag{10}$$

The new conditions still impose orthogonality, but now the conditions only hold for each $\tau$ rather than for each t and $\tau$. Collapsed instruments can be shown to lead to less biased estimates but their standard errors tend to increase (Roodman (2006)). Two specification tests are conducted to verify the validity of the chosen instrument set. Specifically, the Hansen

[20] The use of too many instruments will over fit an endogenous variable and result in poor estimation of the optimal weighting matrix. Roodman(2009) notes it is not uncommon for the optimal weight matrix to become singular and force the use of the generalized inverse.

[21] Collapsed instruments have also been used in the economic growth literature where dynamic panel models of a similar cross-sectional and time dimensions are estimated. See for instance Cauldron et. al (2002), Beck and Levine (2004), and Karcovic and Levine (2005).

test for over identification is performed to verify instrument validity while the Arellano-Bond test is performed to verify the the required assumptions on the absence of serial correlation in the level residuals. The system estimator described above is used to obtain estimates of $\phi$, the reaction function slope parameter, for each of the six policy instruments across the full sample period (1983-2008) and the three distant welfare periods - the AFDC regime, Waiver period, and TANF era.

### 2.3.1 Allowing for Asymmetrical Policy Responses

The idea that a state may respond differently to the policies of their neighbor's given their neighbor's policy action (i.e. benefit increase versus benefit cut) or their relative position (relatively generous or relatively stingy) has taken hold in the welfare and more general fiscal competition literature (Figlio (1999), Bailey and Rom (2004), Fredriksson and Millimet (2002)). The premise has a clear intuitive appeal for researchers attempting to disentangle whether competition or some other competing explanation (yardstick competition, copy-catting, common intellectual trend) is driving the strategic policy behavior. Under the "race to the bottom" scenario one could expect a benefit cut by one state to invoke a larger policy response from neighbors offering relatively more generous benefits than neighbors who already have a low benefit level. I therefore extend the model to allow for asymmetrical state responses. Specifically, equation (2) is written as

$$Y_{it} = \gamma Y_{i,t-1} + \phi_0 I_{it} \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt} + \phi_1 (1 - I_{it}) \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt} + X_{it}\beta + \alpha_i + \delta_t + \epsilon_{it} \quad (11)$$

where

$$I_{it} = \begin{cases} 1 & if\ Y_{it} > \sum_{i \neq j} \omega_{ijt} Y_{jt} \\ 0 & otherwise \end{cases}$$

In doing so, I allow states to be differentially impacted by the changing welfare policies of their neighbor's conditioning on whether their benefits, tax rates, etc. are above or below the weighted average of their neighbors. Under this specification, $\phi_0$ ($\phi_1$) gives the strategic response of states with welfare policies higher (lower) than the weighted average of their neighbors. Wald tests are utilized to determine if response asymmetries are present. Under the null hypothesis, $\phi_0 = \phi_1$, state's respond the same to a neighbor's policy change regardless of their relative position. Rejection of the null hypothesis is consistent with response asymmetries.

### 2.4 Data

To estimate equations (2) and (11), I assemble a panel of data on state welfare policies, demographics, and the macro economic and political environment for the years 1983-2008. For the maximum benefit level I use the state set maximum AFDC (or TANF) benefit level for a family of three collected from the UKCPR's welfare database.[22] To obtain state level estimates of the effective benefit guarantees and tax rates, I implement the reduced-form methodology of Ziliak (2007) which requires the use of administrative micro caseload data.[23] With such data one regresses the actual AFDC/TANF benefit for recipient $i = 1, ...N$, in state $j = 1, ...J$, at time $t = 1, ...T$ on the recipient's earned income, unearned/transfer income and controls for the number of children. State specific and time-varying intercepts combined with coefficients on variables indicating the presence of additional children provide an estimate of the effective benefit guarantee for families of various sizes. The coefficient on the recipients earned income is used to provide estimates of effective tax rates.[24] The caseload data used in constructing these estimates comes from two different administrative sources. The first is the AFDC Quality Control System

[22] www.ukcpr.org/AvailableData.aspx

[23] I am grateful to Jim Ziliak for providing programs and data which allowed me to replicate and extend his 1983-2002 analysis through 2008.

[24] A more detailed explanation of the construction of the effective benefit guarantees and tax rates is contained in the data appendix.

(AFDC-QC), which covers 1983-1997, and the second is the National TANF Data System (NTDS), which covers 1998-2008.[25] Summary statistics for the benefit and tax rate variables are presented in Table 2.1 for the pooled sample and the three separate welfare periods. The geographic distribution of benefit levels is illustrated by Figures 2.5 and 2.6 which map the maximum state benefit levels for the AFDC and TANF periods. Looking at 2.5, the AFDC map, one can see a clear pattern of geographic clustering with the most generous benefits levels located in the New England and west coast and the least generous located in the south. Moving to 2.6, the TANF map, one can see the map lighten as more states join the lower benefit levels.

The final three welfare measures are constructed from data available only for the TANF period. The first of these is the approval rate which I define as the average monthly number of applications approved over the average monthly applications received.[26] The other two variables capture state strictness in removing people from the welfare roles. The first, sanction use, is defined as the percent distribution of TANF closed-case families with cases closed by sanctions. The final variable, non-sanction state policy, is defined as the percent distribution of TANF case-closed families with cases closed by state-policy. Case closure data comes from the Characteristics and Financial Circumstances of TANF Recipients database.[27] Summary statistics for these variables are presented in Table 2.1. Their geographic distributions are displayed in figure 2.7-2.9. From the map, one can tell some states - Idaho, Texas, Florida, Oklahoma, and Maryland, for example - appear very policy stringent by displaying both low access rates and high sanction use. Other states, New York, Pennsylvania, Utah, and Oregon, among others, appear more lenient with higher acceptance rates and very low sanction use.

[25]The NTDS is called the Emergency TANF Data System for the years 1998 and 1999. See Ziliak (2007) for a detailed discussion of the micro data and sample selection criterion. The AFDC-QC data and codebooks for 1983-1997 are available online at http://afdc.urban.org/ while the TANF 1998-2008 data are available online at http://aspe.hhs.gov/ftp/hsp/tanf-data/index.shtml

[26]The application data is available online for the years 2000-2010 at www.acf.hhs.gov/program/ofa/data-reports/caseload/applications/application.htm

[27]Data available for the years 1998-2009 online at http://www.acf.hhs.gov/programs/ofa/character/index.html

The control variables adopted for this analysis are those commonly found in the empirical literature and are meant to capture aspects of each state's economic and political climate as well as characteristics of the low-skill and female labor market. Specifically I control for population, the African American proportion of the population, the poverty rate, the female unemployment rate, median wage, employment per capita, and an indicator for a democratic governor. The African American proportion of the population, median wage, and female unemployment rate are constructed from the Current Population Survey (CPS).[28] The remaining variables come from the UKCPR's welfare database. All variables are measured in 2007 dollars. Descriptive statistics are presented in Table 2.1.

## 2.5 Results

All models are estimated in both a static and dynamic framework. I begin by presenting the results for the benefit and tax rate variables over the full 1983-2008 period and then the three separate welfare periods - AFDC, waiver, and TANF. Results for the remaining variables (access, sanctions, and non sanction state policy) are reported separately as they span a different time period (2000-2008). I report models with and without allowing for response asymmetries. $WY_p$ denotes the spatial coefficient in the model without asymmetries, where different policy instruments are indexed by p. For the model including asymmetries, $WY_p(I_{it})$ denotes the spatial coefficient for states with benefits, tax rates, etc. greater than their neighbors on average, while $WY_p(1 - I_{it})$ is the response of states setting these policies lower than their neighbors on average. Wald tests are presented to indicate whether or not response asymmetries are present. Hansen tests for over identification are presented for all models and consistently fail to reject the null of valid instruments. The Arellono-Bond tests for serial correlation and instrument counts are also reported.

The baseline models use the main contiguity weight matrix, WI. Endogenous spatial variables are instrumented with their second through fourth lags collapsed in all initial

[28] To address the fact that samples sizes can be limited for subpopulations in smaller states, these variables are constructed as three-year moving averages.

models while controls are treated as predetermined and instrumented with their first lag collapse.[29] Estimates of control variables are suppressed for ease of presentation. Full results are available upon request.

### 2.5.1 Static Results

Table 2.2 presents the full period analysis. Evidence of strategic state policy setting is found across all benefit and tax rate variables for the 1983-2008 period. Estimates of the different spatial coefficients are both economically and statistically significant. The magnitude of strategic behavior appears to be largest for the maximum and effective benefit levels. Estimates suggest that states respond to a 10 percent cut in the average benefit level of the their neighbors with an own cut of around 9.3 percent. When allowing for asymmetric responses, I find states are slightly more responsive to cuts in neighbors benefits when their own benefit level is above the weighted average of their neighbors.[30] Though not conclusive evidence, the finding of asymmetries suggests the strategic interaction found is likely due to competitive behavior rather than other phenomenons noted in the literature (yardstick competition, copy-catting, common intellectual trend) or some geographically correlated omitted variable. Or, as stated by Figlio et. al (1999), it appears that "states are more concerned about being left-ahead in welfare benefit levels than they are about being left behind." Strategic policy setting over the effective benefit level is also detected and indicates states respond to a 10 percent cut in neighbor effective benefits with an own cut of 7.5 percent Evidence of competition over the effective benefit suggests states could be strategically using polices such as family caps, partial sanctions, and financial incentives to keep the actual benefits they pay in line with their neighbors. This finding implies there

[29]Estimates are robust to the use of multiple lag structures (see sensitivity analysis located in appendix).

[30]Asymmetry results for the benefit level variables do not produce much of a differential affect and are therefore not of much interest. However, more important asymmetries are detected for the remaining policy instruments. It is also worth noting that while one might expect the main estimate of the spatial coefficient to provide a upper bound (or lower bound) for states below the mean (above the mean), this is not always the case or required econometrically given the time varying nature of whether a state falls above or below the mean.

may exist competition over the benefit base as well as the level. Moving onto the tax rate results, I find that a 10 percent cut in the effective tax rate on earned income by states' neighbors is met with an own state reduction of approximately 8 percent.

Interestingly, the asymmetrical responses to neighbors' effective tax rates on earnings are much larger and economically important than those found for benefits. While at first one might suspect states engaged in competition would increase effective tax rates in order to reduce overall generosity, this is not necessarily the case.[31] Cuts in the effective tax rates coinciding with falling benefits would not do much to increase overall state welfare generosity (especially if one was not working or receiving non-labor income). Instead, one should view the falling effective tax rates on earned income as use of 'carrot' policies by states to lure recipients to the labor market and eventually off welfare. In some sense, the results suggest states are 'racing to force recipients back to work'. A state that finds itself employing an effective tax rate on earned income greater on average than its neighbors, will match a 10 percent cut in neighbors benefits with a own cut of roughly 9 percent. However, if that same state was instead employing an effective tax rate lower than its neighbors, it will only match a 10 percent cut with and own cut of 6.7 percent. Put another way, while states may 'race along' with their neighbors in promoting work, they slow at the prospect of leading this race or being overly generous.

Table 2.3 and 2.4 present results for the three separate welfare regimes. While the full period analysis established evidence of competitive behavior, results produced for this period could mask changes in state behavior occurring after the onset of the waiver period or the 1996 structural shift in the welfare system. For both benefit variables, evidence of competition is found across all three periods. Point estimates suggest benefit competition grew stronger over waiver and TANF periods. For instance, during the AFDC regime, estimates suggest states respond to a 10 percent cut in the maximum benefit level of their neighbor's with an own cut of nearly 7 percent. This magnitude increases to roughly 9.5 percent , and

[31] Falling effective tax rates appears to be the dominant trend in the data making a discussion of "race to the bottom" under this scenario more useful.

8.7 percent for the waiver and TANF periods, respectively. However, when coefficients are tested for equality across periods, I fail to find evidence that they are statistically different from one another. Interestingly, when asymmetries are included, evidence of asymmetrical responses for the maximum benefit level is only found during the TANF era. The effective benefit displays a very similar pattern with asymmetrical responses detected in both the waiver and TANF regimes. With the effective tax rate on earned income, evidence of competition is only found for the AFDC and TANF era. The finding that states implemented very similar tax rates to those of their neighbors under AFDC is perhaps unsurprising given that all states were subject to the same statutory tax rates under this regime. Differentials in state effective tax rates arose primarily due the differences in sources and levels of income disregards permitted by each state. With the onset of the waiver period, states began to experiment by altering their statutory rates and offering further financial incentives. The estimate of strategic policy setting for this period suggests that they did so at first without paying much attention to the policies of bordering states. However under TANF it appears state's did strategically set policies impacting their effective tax rates. Furthermore, the evidence of important asymmetrical responses are only found for the TANF era. These finding suggests several things. First, my previous findings of behavioral asymmetries for the full period were most likely driven by the waiver and TANF periods. Second, after welfare reform, states appear to place more importance on their relative position to their neighbors as one might expect if competition was intensifying.

Table 2.5 presents the results for the final three welfare variables - ease of access, sanction use, and non-sanction state policy. Again, these variables are meant to proxy policy dimensions not captured by the four main policy instruments and are only analyzed for the TANF period. States appear to exhibit strong behavioral responses to their neighbors' approval rates or 'ease of access' to welfare benefits. Specifically, in the model without asymmetrical responses, it appears a state reacts to a 10 percent cut in the weighted average of their neighbors approval rate with an own cut of nearly 8 percent. Setting restrictive access policy could prove ideal for policy makers wishing to offer relatively generous benefits to the worst off without attracting migration. In fact, the inclusion of asymmetries into the model reveals the finding that states already offering more restrictive access relative to their neighbors' respond much stronger to changes in neighbor's policy. The magnitude of the spatial coefficient for states offering relatively more restrictive access is actually double that of the spatial coefficient for their less restrictive counterparts. In other words, if competition is in fact the force behind this strategic behavior, then states choosing to compete through access compete fiercely. The same asymmetry story holds for the sanction and non-sanction state policy variables. This finding is different from the behavior observed over the first four variables. The race to the bottom story consistent with those results was one in which states behave strategically with the goal of keeping their policies in line with those of their neighbors rather that attempting to surge ahead. For the later three variables this is not the case.

### 2.5.2 Dynamic Results

Table 2.6 presents the results for the full period dynamic specification. As one would expect, the lagged dependent variables are highly significant across all policy instruments. Furthermore, they appear to be a principle factor determining a state's policy for the current year. In fact, once controlling for last year's maximum benefit level, all evidence of strategic responses to neighbor policy for this variable disappears (at least for the time frame in question). An explanation for the stark contrast between static and dynamic results is simply that in the case of the maximum benefit level, neighbors benefits are serving as a proxy for own state benefit level. Once controlling for state dependence, neighbors' benefits no longer appear important or, put another way, it no longer appears that states are setting their maximum benefit level strategically. Strategic behavior over the effective benefit level and effective tax rate on earned income remains in the dynamic framework though the spatial coefficients are now reduced in magnitude. The short run effect of a 10 percent cut in the average effective benefit levels of neighboring states leads to an own state reduction of 2.3 percent. In the long run however, this responsiveness grows to nearly 8 percent. For the effective tax rate, the short run response to a ten percent cut by neighbors is an own cut around three percent while the estimated long run coefficient is approximately six percent. Strong evidence of asymmetries are again detected for both the effective benefit variable and tax rate offering further evidence of competition. Figure 2.10 illustrates the dynamic results for both the statutory maximum benefit variable and effective benefit variable by plotting their short run versus long run reaction functions.[32]

Analyzing the three welfare periods separately reveals further evidence of important strategic interaction as well as several interesting patterns. Table 2.7 presents the results for the benefit variables, and 2.8, the results for the effective tax rate. For the maximum benefit guarantee, statistically significant spatial coefficients are only found in the TANF era (and only for the model including asymmetrical responses). However, evidence of strategic interaction does presents in the long run estimates for all three periods suggesting that states may not have set benefit policy simultaneously but they did adjust benefits based upon their neighbors' policies over time. Furthermore, the long run coefficients grow larger across the different periods displaying the same pattern detected in static estimates. Another clear pattern is the growing persistence is state welfare policies. The coefficient on last year's benefits hovered around .7 percent during the AFDC period and then increased to over .9 percent in the TANF regime. Strategic behavior in setting the effective benefit level is more apparent. Though statistically significant spatial coefficients are not found until the TANF period, evidence of strategic behavior over a longer run as well as asymmetrical responses manifest in both the waiver and TANF periods.[33]Taken together these findings suggest the

[32]The predicted benefit levels plotted in the figure are created using the parameters obtained from the static and dynamic models controlling for mean values of the control variables.

[33]The long run coefficients obtained in the TANF period are greater than one indicating an explosive pattern of interaction. This could be taken as evidence of a non-stable equilibrium. Spatial coefficients in excess of one have not been uncommon is the welfare competition literature (See figure 2.4). However, stationarity for spatial dynamic panels requires $|\alpha| \leq 1 - \phi W_{max}$ if $\phi \geq 0$ or that the sum of the spatially and temporally lagged dependent variable is $< 1$ and thus estimates should be viewed with caution.

intensity of strategic behavior over the maximum and effective benefit level grows when moving ahead to the post reform period.

For the effective tax rate, I again find evidence of strategic behavior in both the AFDC and TANF periods but not during the waiver era. Asymmetries are also detected in the periods where strategic behavior occurred and appear to be of clear economic importance during TANF. Specifically, when failing to allow for asymmetrical responses one finds a state responds to a ten percent cut in the average effective tax rate of neighbors with an own cut of 1.2 percent. However, once asymmetries are modeled it appears this behavior occurs mainly among states offering relatively higher tax rates on earned income. These states will match a ten percent cut in neighbors benefits with and own reduction of over five percent while states already offering lower than average tax rates appear unresponsive. This suggests states are strategically manipulating policy parameters used to provide better work incentives. The persistence in the effective tax rates implement by states also appears to be increasing across the periods.

Lastly, Table 2.9 presents the results for the remaining three variables. Evidence of strategic policy setting over these variables does not appear robust to the inclusion of dynamics for the main models. Instead, own state policies last year appear to be the dominant factor in determining current policies. Both the approval rate and sanction use appear to be highly persistent as seen by their sizable coefficients on the lagged dependent variables. However, as before, some evidence is present in the asymmetry models. Here, both sanction use and non-sanction state policy continues to exhibit evidence of short-run strategic policy setting once dynamics are incorporated. Overall results for these models parallel those found in the static analysis again suggesting that states already ahead of their neighbors on average in the use of sanctions and non-sanction state policy are the most responsive to neighbor policy changes.

## 2.6 Sensitivity Analysis

This section presents the results of several sensitivity analyses to explore the robustness of baseline results. Specifically I investigate the sensitivity of the estimation results to the (i) specification of alternative weighting schemes and (ii) additional dynamic considerations.

### 2.6.1 Alternative Weighting Schemes

I compare baseline estimates that used contiguous states as neighbors with those obtained from several additional weighting schemes based on migration flows and distance. The first of these, $W^{Mig}$, assigns each state a weight of $\omega_{ij} = m_{ij}/\sum_i m_{ij}$ where $m_{ij}$ is the number of migrants to state i that resided in state j five years ago. When constructing this matrix, I used 1980 census data (on 1975 to 1980 population flows) to avoid introducing endogeneity into the weighting scheme. $W^{Pov\_Mig}$, and $W^{Edu\_Mig}$ are constructed in the same manner but restricting the migration flows to the population under twice the poverty line and the population with less than a high school education, respectively. For illustration, Figure 2.11 shows the weight matrix constructed from the migration flows of the population under twice the poverty line. The vertical column of state names represents the destination state while the top row across represents the state where the migrant previously resided.The matrix is row normalized so that each row sums to one. Reading across the first row, for example, demonstrates that under one percent of migrants to Alabama came from Arizona while roughly fifteen percent came from Florida, and eleven percent from Georgia. I estimate models using both a restricted form of these weighting schemes where a state continues to only consider its contiguous neighbors, and an unrestricted form where all states are given weight as long as $m_{ij} \neq 0$. A final weight matrix, $W^{Dist}$, is a distance matrix. Here, the off-diagonal elements $\omega_{ij}$ are equal to $(1/d_{ij})/\sum_{j\in J_i}(1/d_{jk})$ where $d_{ij}$ is the distance in kilometers between state centroids if $d_{ij}$ is less than 1000 kilometer and zero otherwise. Under this scheme states consider the policies of a wider set of geographic neighbors. For simplicity I focus on the three main variables over the full 1983-2008 period. Results for both the static and dynamic models are presented in Table 2.10.

Overall, results for both the static and dynamic models appear robust to different migration based contiguity weighting schemes. For instance, moving from the contiguity weighting scheme to the migration or poverty based migration contiguity weighting scheme reduces the spatial coefficient on the maximum benefit from .926 to approximately .86, or roughly 7 percent. However, once one extends the "neighborhood" to include all states, little evidence of competition remains – especially for the benefit level variables. For the most part, spatial coefficients are reduced in magnitude and lose statistical significance suggesting states are most responsive to the maximum benefit levels set by their immediate neighbors. These results are consistent with neighboring states engaged in strategic policy setting rather than states simply following a regional or national trend. Interestingly, the effective tax rate does continue to display some evidence of strategic interaction under the unrestricted weighting schemes.

### 2.6.2 Additional Dynamics

In the standard empirical models of fiscal competition, governments set policies based on those being simultaneously set by their neighbors. However, it is very possible that it takes time for states to learn about and respond to changes in their neighbor's policies. If this is indeed the case, then we might observe states strategically setting policies based on those of their neighbors in period t-1 rather than period t. The short and long run coefficients estimated under the previous dynamic specifications provide us a better understating of the magnitude of the immediate response versus the longer run response that captures these policy adjustments. However, by including additional lags of neighbor's policies in the reaction function, we can gain further insight into the timing state policy responses.

Here I perform I perform two additional analyses incorporating state responses to neighbor's past policies. In the first, I begin with the static model but replace neighbor's policy, $\sum_{i \neq j}^{48} \omega_{ij} Y_{jt}$, with neighbor's policy in t-1, $\sum_{i \neq j}^{48} \omega_{ij} Y_{jt-1}$. Results are shown in Table 2.11

which compares which compares baseline estimates of a state's response to their neighbor's concurrent policies (lag 0) with their estimated response to neighbor's policy in t-1 (lag 1).[34]

Second, I modify the dynamic specification to include additional lags of neighbor's policy. Equation (12) shown below augments equation (4) by including neighbors policy last year.[35] The inclusion of additional spatial lags can capture the delayed response of states to their neighbor's policy changes.

$$\Delta Y_{it} = \gamma \Delta Y_{it-1} + \phi_0 \Delta \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt} + \phi_1 \Delta \sum_{i \neq j}^{48} \omega_{ijt} Y_{jt-1} + \Delta X_{it}\beta + \Delta\delta_t + \Delta\varepsilon_{it} \quad (12)$$

Table 2.11 contains the static estimation results. Coefficients on neighbor's policy in t-1 are smaller than coefficients on concurrent policies (by roughly twenty percent in the case of the maximum benefit level and less than five percent for the effective benefit and tax rate). Table 2.12 contains the dynamic estimation results. For each variable, the first column contains the base line results while the second column contains the results when neighbor's concurrent policy is replaced with neighbor's policy in t-1. The third column contains results when both concurrent and lagged neighbor policy are included together. I again find significant evidence of strategic policy setting for both the effective benefit level and the effective tax rate on earned income. Results are very similar when concurrent policy is replaced with lagged policy. For the model with neighbor's policy in both period t and t-1, the inclusion of addition spatial lags tend to increase the spatial coefficient on neighbors concurrent benefit level while the additional spatial lag terms are negative – suggestive of a policy adjustment process taking place over several periods. The calculated long run coefficients remain consistent with those produced by the baseline models.

[34] As in the case with the lagged dependent variable, neighbor's policy in period t-1 remains correlated with the error term and is therefore instrumented in the same manner.

[35] Long run coefficients are now calculated as $\frac{\phi_0+\phi_1}{1-\gamma}$.

Thus, the inclusion of additional dynamics does not alter conclusions drawn from previous results.

## 2.7 Conclusion

Using a new spatial econometric approach, this analysis has examined interstate welfare competition over the old AFDC regime, the waiver period, and the first decade of the new TANF era. The estimates suggest that interstate competition was present across all three periods and strongest during the waiver and TANF periods. Long run estimates, which allow for states to adjust to their neighbor's policies over time, are also largest in the waiver and TANF era consistent with a race to the bottom after welfare reform. The results obtained for the effective benefit level and tax rate suggest strategic policy setting occurs in both the benefit level and base. Moreover, response asymmetries indicate states appear more concerned about being relatively generous than relatively stingy when compared with neighbor's in the provision of benefits and work incentives. Lastly, estimates for the approval rate, sanction use, and non-sanction state policy imply states also strategically set policies affecting the extensive margin of program generosity. Interestingly, response asymmetries found for the approval rate, sanction use, and non-sanction state policy indicate states competing on these margins may want to be leaders in the "race to the bottom" rather than just staying in line with neighbor's as was the case with the effective benefit and tax rate. Together, the sizable spatial coefficient found in the static analysis and the long run coefficients produced from the dynamic specifications suggest strategic policy setting was an important factor behind downward trends in welfare generosity.

The fact that states appear highly responsive to the welfare policies of their neighbors may pose cause for concern in today's fiscal climate. Motivated by looming budgetary problems, many states have had to enact deep cuts in their welfare programs. According to a report produced by the Center on Budget and Policy Priorities, in 2011 alone at least five states including California, Washington, New Mexico, South Carolina, and the District of

Columbia cut their monthly benefit levels in a substantial way.[36] For instance, Washington's monthly benefit for a family of three was slashed by $84 dollars while South Carolina's dropped by twenty percent to $217 - an amount corresponding to only fourteen percent of the federal poverty line. At the same time, multiple states adopted shorter or more restrictive time limits and cut financial work incentives. California, for instance, cut its time limit from sixty to forty-eight months and reduced their $225 earning's disregard to $112. Michigan tightened its time limit and scaled back its refundable EITC (partially funded by TANF) from twenty percent of the federal credit to only six percent. Results from the empirical analysis are consistent with states strategically responding to policy changes such as these suggesting we may see a continued reduction in the generosity of state welfare programs.

[36] Schott and Pavetti (2011)

**Figure 2.1 Maximum vs. Effective Benefits**
**(for a family of 3)**

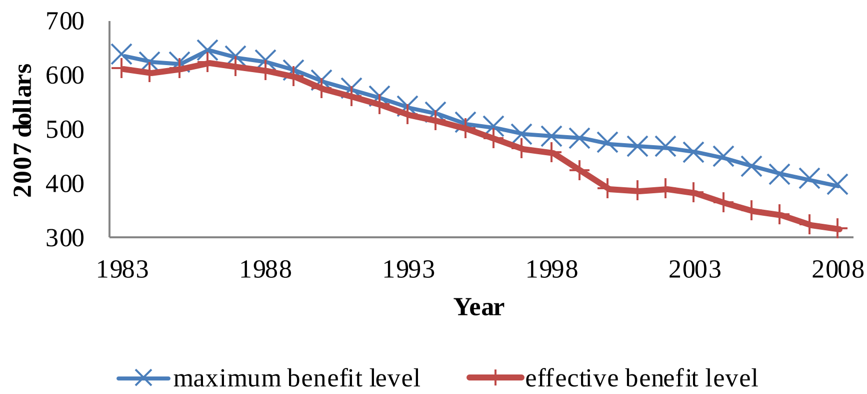



**Figure 2.2 The Effective Tax Rate on Earned Income**

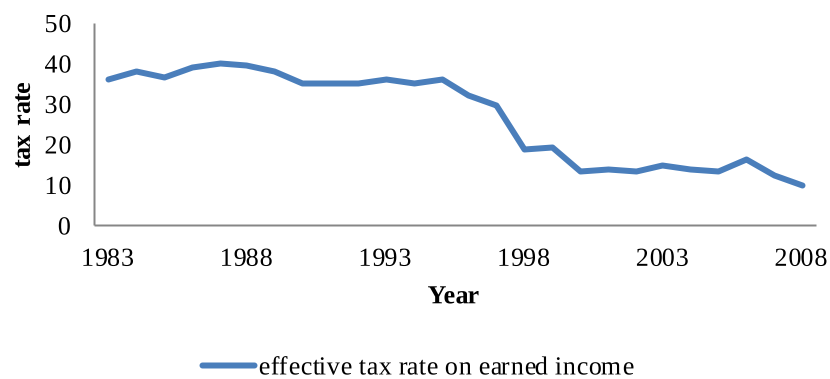



**Figure 2.3 Access to Benefits and Sanction Use**

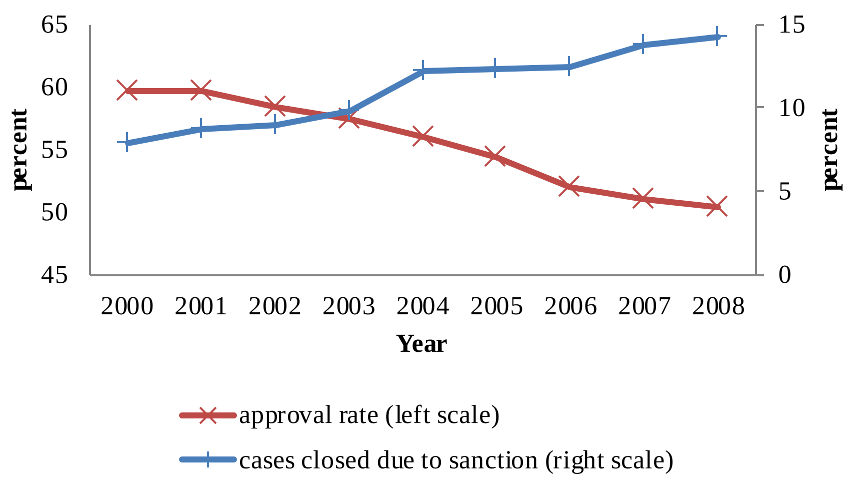


**Figure 2.4 Survey of Welfare Competition Empirical Strategies**

| Author (Date) | Data/years | Dependent Variable | Main Weight Matrix | Model/Estimation technique | Spatial Coefficient Estimates (ρ) |
|---|---|---|---|---|---|
| Dahlberg & Edmark (2008) | 281 Swedish Municipalities 1989-1994 | Benefit Expenditure per recipient | contiguity | $B_t = \rho W B_t + \beta X_t + \delta W X_t + \varepsilon_t$ ; IV | .648-1.519 |
| Figlio et. al (1999) | Continental U.S. 1983-1994 | Combined maximum AFDC and Food Stamp benefit for family of 3 | Based on state to state migration flows | $B_t = \rho \Delta W B_t + \beta \Delta X_t + \varepsilon_t$ & $B_t = \rho \Delta W B_t + \beta \Delta X_t + \rho \Delta W B_t * I_t + \varepsilon_t$ ; IV | .904-1.314 |
| Fiva & Rattso (2006) | 433 Norwegian Municipalities in 1998 | Expected welfare benefit of standardized recipient, benefit norm for 1 | contiguity | $B_t = \rho W B_t + \beta X_t + \varepsilon_t$ ; IV & reduced form | .36-.81 |
| Saavedra (2000) | Continental U.S. 1985, 1990, 1995 – separate cross section & pooled | Maximum AFDC benefit for family of 3 | contiguity | $B_t = \rho W B_t + \beta X_t + \varepsilon_t$ ; reduced form | .21-1.35 |
| Rom et. al (1998) | Continental U.S. 1976-1994 | Maximum AFDC benefit for family of 4 | contiguity | $B_t = \rho W B_t + \gamma B_{t-1} + \beta X_t + \varepsilon_t$ ; reduced form | .274 |

Table notes: All reported coefficients are statistically significant at 90% confidence level.

**Figure 2.5 Maximum Benefit for a Family of 3 under AFDC**

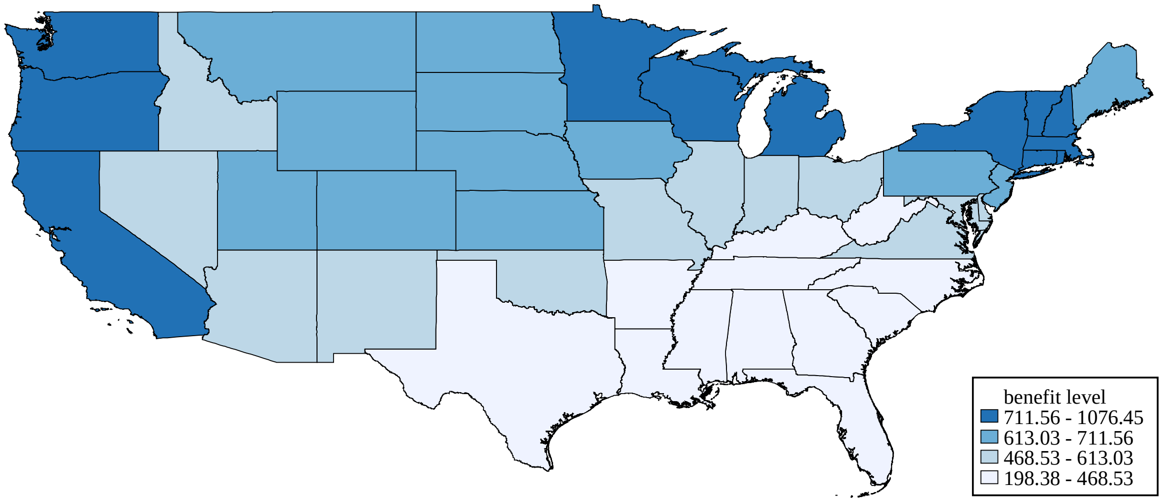



**Figure 2.6 Maximum Benefit for a Family of 3 under TANF**

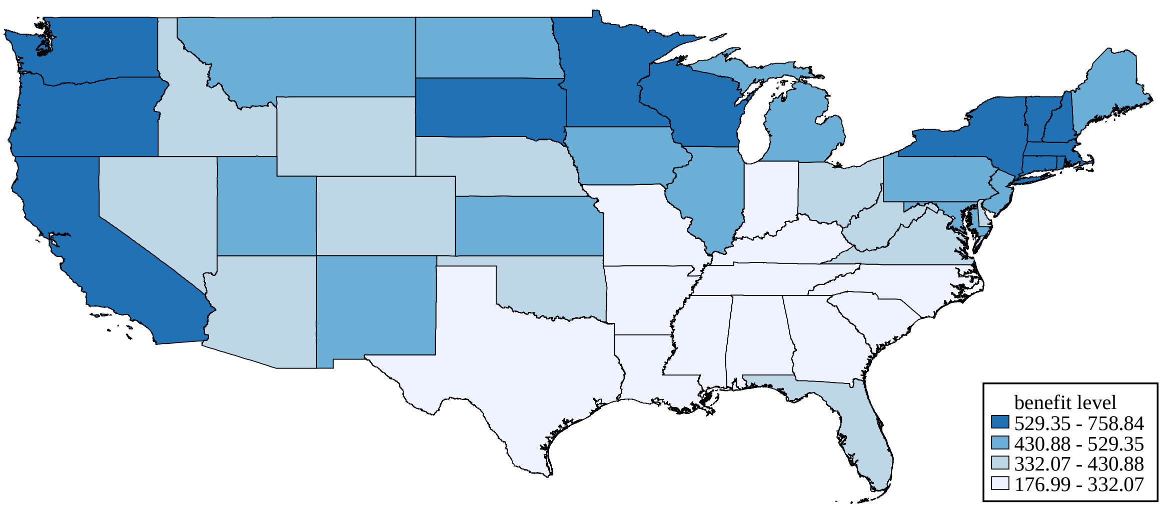


**Figure 2.7 Acceptance Rate (2000-2008)**

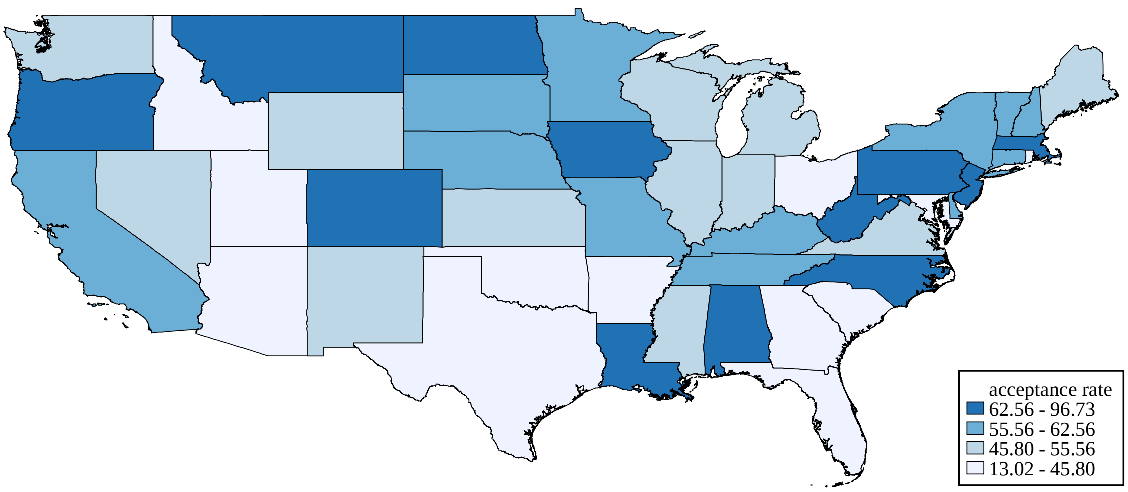



**Figure 2.8 Percent Distribution of Cases Closed by Sanction (2000-2008)**

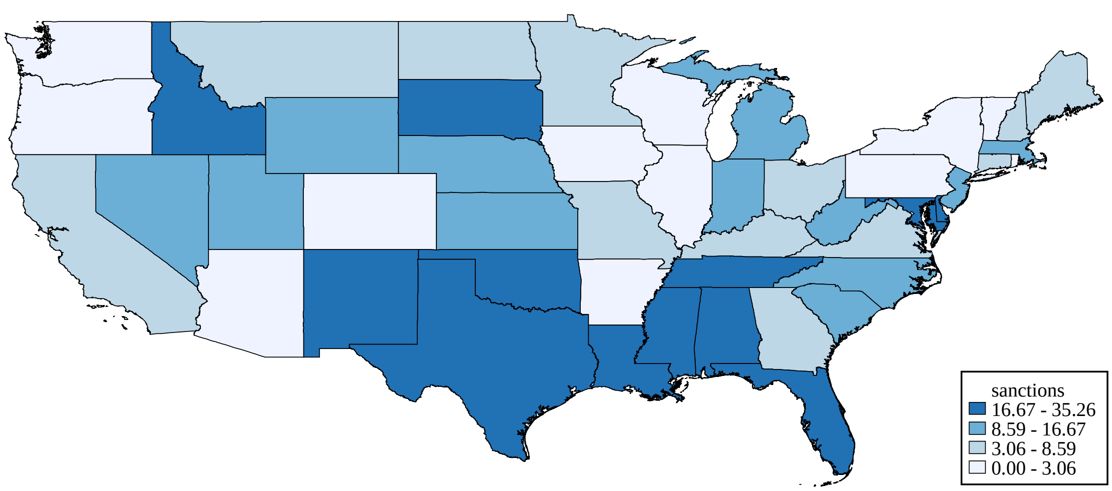
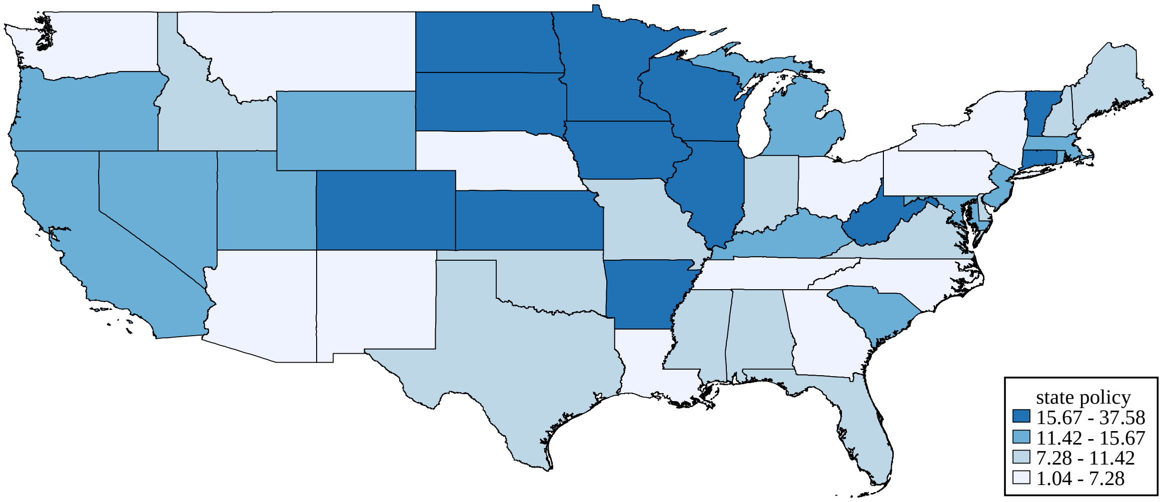


**Figure 2.9 Percent Distribution of Cases Closed by Non-Federal Non-Sanction Policy (2000-2008)**



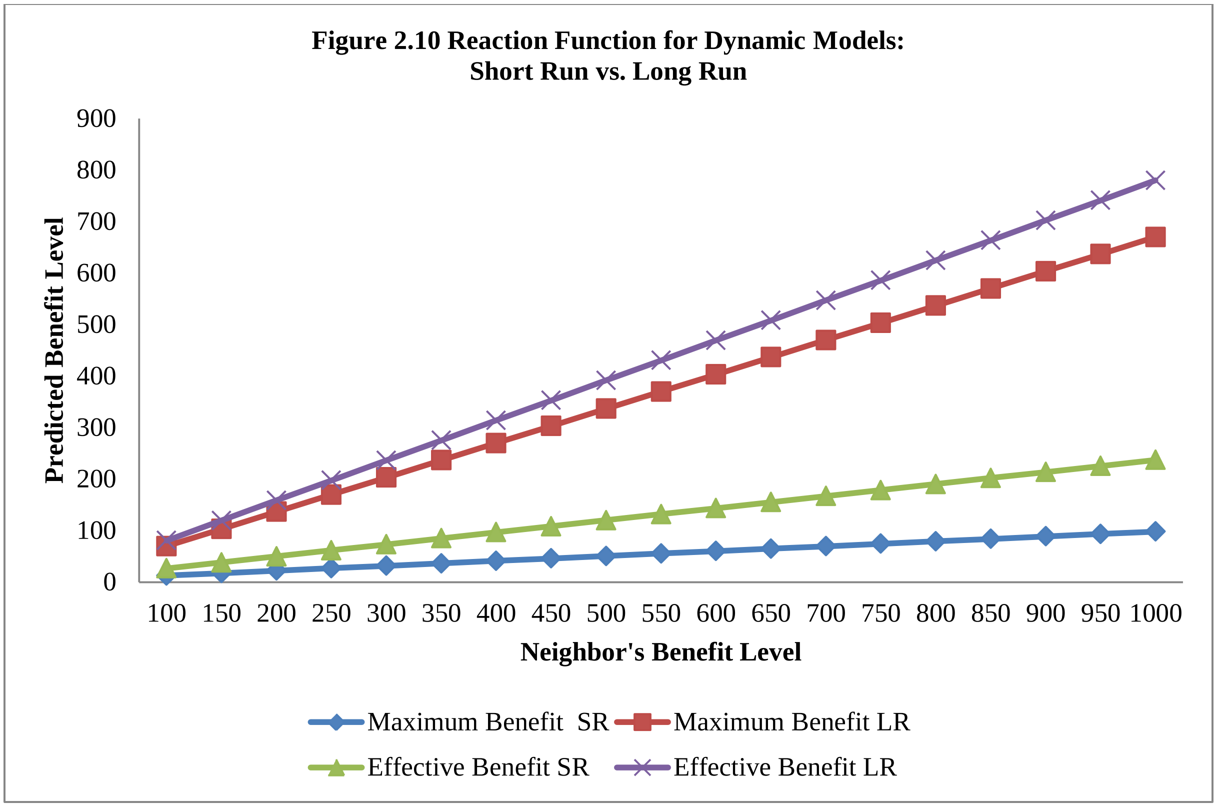


Figure 2.10 Reaction Function for Dynamic Models:
Short Run vs. Long Run
Predicted Benefit Level
0
100
200
300
400
500
600
700
800
900
100 150 200 250 300 350 400 450 500 550 600 650 700 750 800 850 900 950 1000
Neighbor's Benefit Level
Maximum Benefit SR
Maximum Benefit LR
Effective Benefit SR
Effective Benefit LR

**Figure 2.11 Poverty Migration Based Weight Matrix (Unrestricted Distance Version)**

| | AL | AZ | AR | CA | CO | CT | DE | FL | GA | ID | IL | IN | IA | KS | KY | LA | ME |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AL | 0.000 | 0.009 | 0.015 | 0.070 | 0.015 | 0.009 | 0.004 | 0.146 | 0.114 | 0.000 | 0.026 | 0.023 | 0.008 | 0.010 | 0.023 | 0.046 | 0.003 |
| AZ | 0.005 | 0.000 | 0.027 | 0.241 | 0.047 | 0.001 | 0.000 | 0.031 | 0.010 | 0.017 | 0.023 | 0.018 | 0.012 | 0.020 | 0.007 | 0.013 | 0.003 |
| AR | 0.008 | 0.017 | 0.000 | 0.077 | 0.013 | 0.000 | 0.001 | 0.050 | 0.021 | 0.000 | 0.042 | 0.017 | 0.012 | 0.024 | 0.007 | 0.060 | 0.001 |
| CA | 0.009 | 0.069 | 0.023 | 0.000 | 0.042 | 0.004 | 0.001 | 0.038 | 0.008 | 0.030 | 0.026 | 0.011 | 0.010 | 0.017 | 0.007 | 0.015 | 0.003 |
| CO | 0.006 | 0.065 | 0.015 | 0.122 | 0.000 | 0.006 | 0.002 | 0.026 | 0.014 | 0.019 | 0.035 | 0.013 | 0.014 | 0.041 | 0.005 | 0.008 | 0.006 |
| CT | 0.008 | 0.027 | 0.006 | 0.091 | 0.020 | 0.000 | 0.007 | 0.166 | 0.015 | 0.006 | 0.013 | 0.013 | 0.002 | 0.001 | 0.001 | 0.003 | 0.037 |
| DE | 0.000 | 0.028 | 0.006 | 0.050 | 0.028 | 0.028 | 0.000 | 0.133 | 0.028 | 0.006 | 0.044 | 0.011 | 0.000 | 0.006 | 0.011 | 0.011 | 0.006 |
| FL | 0.050 | 0.017 | 0.011 | 0.075 | 0.016 | 0.008 | 0.005 | 0.000 | 0.114 | 0.003 | 0.027 | 0.030 | 0.004 | 0.005 | 0.021 | 0.017 | 0.008 |
| GA | 0.101 | 0.010 | 0.011 | 0.048 | 0.015 | 0.002 | 0.002 | 0.196 | 0.000 | 0.002 | 0.020 | 0.012 | 0.003 | 0.005 | 0.021 | 0.020 | 0.001 |
| ID | 0.005 | 0.030 | 0.005 | 0.121 | 0.014 | 0.000 | 0.000 | 0.011 | 0.002 | 0.000 | 0.009 | 0.002 | 0.002 | 0.009 | 0.000 | 0.009 | 0.000 |
| IL | 0.014 | 0.051 | 0.031 | 0.116 | 0.027 | 0.003 | 0.000 | 0.113 | 0.020 | 0.003 | 0.000 | 0.049 | 0.032 | 0.008 | 0.022 | 0.014 | 0.001 |
| IN | 0.016 | 0.044 | 0.015 | 0.076 | 0.021 | 0.002 | 0.000 | 0.148 | 0.021 | 0.002 | 0.094 | 0.000 | 0.005 | 0.013 | 0.085 | 0.006 | 0.002 |
| IA | 0.004 | 0.041 | 0.029 | 0.083 | 0.059 | 0.004 | 0.000 | 0.040 | 0.010 | 0.003 | 0.074 | 0.016 | 0.000 | 0.027 | 0.008 | 0.005 | 0.000 |
| KS | 0.007 | 0.031 | 0.034 | 0.080 | 0.066 | 0.005 | 0.000 | 0.025 | 0.009 | 0.005 | 0.022 | 0.019 | 0.022 | 0.000 | 0.011 | 0.009 | 0.000 |
| KY | 0.022 | 0.012 | 0.008 | 0.066 | 0.014 | 0.002 | 0.001 | 0.097 | 0.029 | 0.001 | 0.046 | 0.128 | 0.001 | 0.008 | 0.000 | 0.012 | 0.005 |
| LA | 0.036 | 0.010 | 0.028 | 0.114 | 0.018 | 0.001 | 0.000 | 0.065 | 0.025 | 0.001 | 0.025 | 0.015 | 0.003 | 0.014 | 0.010 | 0.000 | 0.001 |
| ME | 0.013 | 0.032 | 0.003 | 0.073 | 0.019 | 0.029 | 0.006 | 0.099 | 0.013 | 0.000 | 0.022 | 0.013 | 0.010 | 0.006 | 0.006 | 0.003 | 0.000 |
| MD | 0.007 | 0.009 | 0.005 | 0.070 | 0.013 | 0.015 | 0.036 | 0.120 | 0.025 | 0.000 | 0.014 | 0.006 | 0.002 | 0.007 | 0.005 | 0.012 | 0.007 |
| MA | 0.007 | 0.025 | 0.001 | 0.114 | 0.018 | 0.041 | 0.005 | 0.148 | 0.017 | 0.001 | 0.012 | 0.003 | 0.002 | 0.004 | 0.003 | 0.010 | 0.058 |
| MI | 0.023 | 0.047 | 0.019 | 0.118 | 0.027 | 0.005 | 0.001 | 0.147 | 0.028 | 0.006 | 0.045 | 0.050 | 0.007 | 0.004 | 0.026 | 0.008 | 0.001 |
| MN | 0.002 | 0.054 | 0.006 | 0.105 | 0.047 | 0.002 | 0.000 | 0.042 | 0.008 | 0.010 | 0.038 | 0.010 | 0.053 | 0.007 | 0.006 | 0.007 | 0.002 |
| MS | 0.066 | 0.009 | 0.032 | 0.063 | 0.007 | 0.001 | 0.003 | 0.069 | 0.021 | 0.001 | 0.093 | 0.013 | 0.003 | 0.009 | 0.013 | 0.110 | 0.003 |
| MO | 0.007 | 0.029 | 0.065 | 0.099 | 0.035 | 0.002 | 0.000 | 0.048 | 0.014 | 0.008 | 0.107 | 0.020 | 0.034 | 0.101 | 0.009 | 0.015 | 0.001 |
| MT | 0.007 | 0.050 | 0.013 | 0.089 | 0.079 | 0.003 | 0.000 | 0.017 | 0.007 | 0.053 | 0.013 | 0.000 | 0.007 | 0.010 | 0.007 | 0.003 | 0.000 |
| NE | 0.006 | 0.030 | 0.026 | 0.110 | 0.119 | 0.004 | 0.000 | 0.026 | 0.006 | 0.004 | 0.006 | 0.004 | 0.134 | 0.087 | 0.002 | 0.013 | 0.006 |
| NV | 0.003 | 0.038 | 0.013 | 0.373 | 0.030 | 0.000 | 0.000 | 0.028 | 0.003 | 0.060 | 0.013 | 0.005 | 0.015 | 0.008 | 0.003 | 0.015 | 0.005 |
| NH | 0.010 | 0.022 | 0.000 | 0.051 | 0.013 | 0.041 | 0.003 | 0.121 | 0.016 | 0.010 | 0.006 | 0.000 | 0.003 | 0.016 | 0.003 | 0.010 | 0.105 |
| NJ | 0.007 | 0.023 | 0.002 | 0.086 | 0.012 | 0.022 | 0.010 | 0.212 | 0.025 | 0.003 | 0.012 | 0.005 | 0.003 | 0.001 | 0.010 | 0.008 | 0.012 |
| NM | 0.004 | 0.081 | 0.015 | 0.132 | 0.083 | 0.002 | 0.000 | 0.023 | 0.009 | 0.013 | 0.009 | 0.004 | 0.004 | 0.019 | 0.015 | 0.013 | 0.006 |
| NY | 0.012 | 0.028 | 0.003 | 0.120 | 0.023 | 0.030 | 0.003 | 0.243 | 0.026 | 0.002 | 0.015 | 0.008 | 0.003 | 0.005 | 0.005 | 0.007 | 0.005 |
| NC | 0.025 | 0.014 | 0.009 | 0.064 | 0.012 | 0.008 | 0.002 | 0.112 | 0.084 | 0.002 | 0.018 | 0.011 | 0.005 | 0.008 | 0.015 | 0.012 | 0.005 |
| ND | 0.004 | 0.033 | 0.000 | 0.083 | 0.046 | 0.008 | 0.004 | 0.042 | 0.025 | 0.025 | 0.013 | 0.008 | 0.017 | 0.025 | 0.000 | 0.013 | 0.000 |
| OH | 0.016 | 0.043 | 0.008 | 0.084 | 0.023 | 0.005 | 0.002 | 0.185 | 0.025 | 0.003 | 0.036 | 0.050 | 0.004 | 0.007 | 0.073 | 0.009 | 0.003 |
| OK | 0.015 | 0.024 | 0.078 | 0.099 | 0.053 | 0.001 | 0.000 | 0.020 | 0.018 | 0.006 | 0.018 | 0.006 | 0.010 | 0.068 | 0.015 | 0.018 | 0.005 |
| OR | 0.000 | 0.043 | 0.013 | 0.273 | 0.032 | 0.000 | 0.001 | 0.018 | 0.005 | 0.071 | 0.014 | 0.012 | 0.016 | 0.005 | 0.003 | 0.001 | 0.001 |
| PA | 0.009 | 0.024 | 0.003 | 0.090 | 0.020 | 0.012 | 0.023 | 0.154 | 0.019 | 0.000 | 0.018 | 0.013 | 0.003 | 0.004 | 0.008 | 0.008 | 0.006 |
| RI | 0.007 | 0.011 | 0.000 | 0.092 | 0.028 | 0.043 | 0.000 | 0.106 | 0.018 | 0.004 | 0.025 | 0.004 | 0.000 | 0.004 | 0.004 | 0.004 | 0.043 |
| SC | 0.023 | 0.012 | 0.008 | 0.059 | 0.005 | 0.009 | 0.001 | 0.095 | 0.122 | 0.005 | 0.016 | 0.013 | 0.005 | 0.004 | 0.013 | 0.016 | 0.004 |
| SD | 0.004 | 0.052 | 0.008 | 0.104 | 0.060 | 0.000 | 0.000 | 0.016 | 0.004 | 0.016 | 0.012 | 0.008 | 0.056 | 0.028 | 0.004 | 0.000 | 0.000 |
| TN | 0.056 | 0.012 | 0.036 | 0.065 | 0.013 | 0.002 | 0.002 | 0.094 | 0.107 | 0.000 | 0.036 | 0.029 | 0.002 | 0.011 | 0.061 | 0.023 | 0.002 |
| TX | 0.020 | 0.024 | 0.054 | 0.174 | 0.042 | 0.007 | 0.001 | 0.051 | 0.023 | 0.007 | 0.026 | 0.018 | 0.008 | 0.025 | 0.013 | 0.071 | 0.003 |
| UT | 0.003 | 0.079 | 0.003 | 0.223 | 0.059 | 0.000 | 0.000 | 0.015 | 0.005 | 0.092 | 0.015 | 0.010 | 0.003 | 0.008 | 0.003 | 0.010 | 0.005 |
| VT | 0.005 | 0.016 | 0.000 | 0.064 | 0.032 | 0.027 | 0.000 | 0.181 | 0.005 | 0.000 | 0.011 | 0.000 | 0.005 | 0.000 | 0.005 | 0.016 | 0.053 |
| VA | 0.016 | 0.011 | 0.005 | 0.078 | 0.014 | 0.011 | 0.007 | 0.100 | 0.040 | 0.003 | 0.019 | 0.013 | 0.003 | 0.006 | 0.018 | 0.008 | 0.006 |
| WA | 0.007 | 0.047 | 0.008 | 0.217 | 0.022 | 0.003 | 0.002 | 0.025 | 0.006 | 0.066 | 0.021 | 0.006 | 0.004 | 0.013 | 0.008 | 0.005 | 0.001 |
| WV | 0.021 | 0.019 | 0.006 | 0.045 | 0.004 | 0.004 | 0.002 | 0.117 | 0.028 | 0.000 | 0.019 | 0.023 | 0.004 | 0.004 | 0.049 | 0.004 | 0.000 |
| WI | 0.007 | 0.044 | 0.012 | 0.121 | 0.030 | 0.002 | 0.000 | 0.080 | 0.008 | 0.008 | 0.102 | 0.022 | 0.031 | 0.012 | 0.001 | 0.006 | 0.001 |
| WY | 0.008 | 0.037 | 0.012 | 0.091 | 0.156 | 0.004 | 0.000 | 0.021 | 0.004 | 0.049 | 0.021 | 0.008 | 0.021 | 0.008 | 0.004 | 0.016 | 0.008 |

**Figure 2.11 Continued**

| MD | MA | MI | MN | MS | MO | MT | NE | NV | NH | NJ | NM | NY | NC | ND | OH | OK | OR | PA | RI | SC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.005 | 0.003 | 0.036 | 0.001 | 0.073 | 0.012 | 0.001 | 0.004 | 0.004 | 0.000 | 0.008 | 0.001 | 0.022 | 0.024 | 0.000 | 0.032 | 0.013 | 0.000 | 0.010 | 0.000 | 0.028 |
| 0.004 | 0.007 | 0.022 | 0.013 | 0.004 | 0.026 | 0.004 | 0.007 | 0.026 | 0.004 | 0.005 | 0.037 | 0.021 | 0.016 | 0.003 | 0.029 | 0.025 | 0.032 | 0.017 | 0.002 | 0.004 |
| 0.005 | 0.003 | 0.036 | 0.005 | 0.037 | 0.093 | 0.004 | 0.007 | 0.004 | 0.000 | 0.003 | 0.016 | 0.008 | 0.009 | 0.000 | 0.016 | 0.110 | 0.008 | 0.005 | 0.001 | 0.007 |
| 0.007 | 0.012 | 0.018 | 0.014 | 0.006 | 0.028 | 0.013 | 0.010 | 0.047 | 0.002 | 0.008 | 0.022 | 0.029 | 0.016 | 0.004 | 0.018 | 0.034 | 0.102 | 0.020 | 0.002 | 0.006 |
| 0.005 | 0.004 | 0.026 | 0.019 | 0.005 | 0.040 | 0.019 | 0.032 | 0.013 | 0.002 | 0.008 | 0.045 | 0.021 | 0.011 | 0.010 | 0.016 | 0.043 | 0.034 | 0.008 | 0.000 | 0.006 |
| 0.011 | 0.115 | 0.007 | 0.001 | 0.001 | 0.003 | 0.003 | 0.000 | 0.004 | 0.027 | 0.022 | 0.007 | 0.113 | 0.043 | 0.000 | 0.015 | 0.000 | 0.007 | 0.029 | 0.031 | 0.019 |
| 0.139 | 0.006 | 0.006 | 0.011 | 0.017 | 0.000 | 0.000 | 0.006 | 0.000 | 0.000 | 0.039 | 0.000 | 0.028 | 0.011 | 0.000 | 0.011 | 0.017 | 0.011 | 0.161 | 0.006 | 0.022 |
| 0.016 | 0.020 | 0.033 | 0.007 | 0.017 | 0.013 | 0.001 | 0.004 | 0.006 | 0.005 | 0.026 | 0.007 | 0.066 | 0.058 | 0.003 | 0.046 | 0.011 | 0.007 | 0.027 | 0.003 | 0.030 |
| 0.015 | 0.008 | 0.017 | 0.005 | 0.017 | 0.016 | 0.002 | 0.004 | 0.006 | 0.002 | 0.013 | 0.005 | 0.034 | 0.056 | 0.004 | 0.020 | 0.010 | 0.004 | 0.017 | 0.001 | 0.056 |
| 0.002 | 0.002 | 0.014 | 0.009 | 0.000 | 0.014 | 0.046 | 0.007 | 0.027 | 0.000 | 0.002 | 0.005 | 0.005 | 0.005 | 0.007 | 0.007 | 0.014 | 0.117 | 0.002 | 0.000 | 0.009 |
| 0.002 | 0.009 | 0.043 | 0.020 | 0.023 | 0.058 | 0.003 | 0.005 | 0.007 | 0.001 | 0.006 | 0.009 | 0.020 | 0.012 | 0.001 | 0.019 | 0.010 | 0.009 | 0.008 | 0.001 | 0.006 |
| 0.008 | 0.007 | 0.060 | 0.008 | 0.008 | 0.021 | 0.002 | 0.007 | 0.008 | 0.000 | 0.004 | 0.005 | 0.019 | 0.017 | 0.006 | 0.060 | 0.013 | 0.008 | 0.016 | 0.001 | 0.011 |
| 0.005 | 0.004 | 0.012 | 0.079 | 0.001 | 0.107 | 0.007 | 0.086 | 0.005 | 0.000 | 0.004 | 0.018 | 0.008 | 0.007 | 0.004 | 0.014 | 0.018 | 0.022 | 0.007 | 0.000 | 0.004 |
| 0.005 | 0.005 | 0.009 | 0.010 | 0.005 | 0.188 | 0.006 | 0.036 | 0.006 | 0.001 | 0.001 | 0.014 | 0.015 | 0.007 | 0.004 | 0.011 | 0.120 | 0.017 | 0.005 | 0.002 | 0.009 |
| 0.006 | 0.004 | 0.036 | 0.006 | 0.011 | 0.020 | 0.001 | 0.005 | 0.001 | 0.001 | 0.008 | 0.005 | 0.020 | 0.040 | 0.001 | 0.150 | 0.006 | 0.007 | 0.012 | 0.000 | 0.009 |
| 0.007 | 0.004 | 0.010 | 0.008 | 0.131 | 0.014 | 0.006 | 0.006 | 0.015 | 0.001 | 0.000 | 0.008 | 0.010 | 0.019 | 0.001 | 0.010 | 0.026 | 0.007 | 0.010 | 0.001 | 0.010 |
| 0.006 | 0.089 | 0.013 | 0.010 | 0.003 | 0.013 | 0.003 | 0.006 | 0.003 | 0.131 | 0.010 | 0.019 | 0.057 | 0.019 | 0.003 | 0.010 | 0.013 | 0.010 | 0.029 | 0.019 | 0.016 |
| 0.000 | 0.025 | 0.015 | 0.005 | 0.006 | 0.010 | 0.005 | 0.005 | 0.009 | 0.005 | 0.015 | 0.008 | 0.035 | 0.065 | 0.000 | 0.018 | 0.009 | 0.010 | 0.100 | 0.005 | 0.023 |
| 0.015 | 0.000 | 0.015 | 0.009 | 0.003 | 0.007 | 0.003 | 0.001 | 0.005 | 0.110 | 0.017 | 0.006 | 0.102 | 0.019 | 0.001 | 0.017 | 0.003 | 0.008 | 0.025 | 0.032 | 0.007 |
| 0.005 | 0.009 | 0.000 | 0.008 | 0.013 | 0.021 | 0.003 | 0.004 | 0.005 | 0.001 | 0.006 | 0.008 | 0.028 | 0.022 | 0.003 | 0.062 | 0.008 | 0.013 | 0.019 | 0.001 | 0.009 |
| 0.002 | 0.011 | 0.022 | 0.000 | 0.003 | 0.017 | 0.026 | 0.013 | 0.011 | 0.001 | 0.002 | 0.008 | 0.016 | 0.005 | 0.088 | 0.016 | 0.021 | 0.021 | 0.005 | 0.002 | 0.007 |
| 0.007 | 0.003 | 0.040 | 0.006 | 0.000 | 0.025 | 0.001 | 0.007 | 0.003 | 0.000 | 0.004 | 0.003 | 0.012 | 0.019 | 0.001 | 0.025 | 0.015 | 0.004 | 0.013 | 0.001 | 0.010 |
| 0.002 | 0.004 | 0.021 | 0.011 | 0.013 | 0.000 | 0.005 | 0.017 | 0.011 | 0.001 | 0.004 | 0.014 | 0.013 | 0.008 | 0.003 | 0.016 | 0.068 | 0.015 | 0.008 | 0.000 | 0.005 |
| 0.007 | 0.003 | 0.010 | 0.046 | 0.000 | 0.007 | 0.000 | 0.026 | 0.013 | 0.003 | 0.003 | 0.003 | 0.017 | 0.010 | 0.043 | 0.007 | 0.017 | 0.076 | 0.010 | 0.000 | 0.003 |
| 0.002 | 0.006 | 0.009 | 0.022 | 0.009 | 0.043 | 0.017 | 0.000 | 0.002 | 0.000 | 0.000 | 0.004 | 0.011 | 0.009 | 0.006 | 0.011 | 0.032 | 0.024 | 0.000 | 0.000 | 0.004 |
| 0.000 | 0.003 | 0.010 | 0.013 | 0.003 | 0.005 | 0.005 | 0.005 | 0.000 | 0.003 | 0.008 | 0.013 | 0.013 | 0.013 | 0.000 | 0.013 | 0.018 | 0.070 | 0.008 | 0.003 | 0.003 |
| 0.006 | 0.220 | 0.010 | 0.003 | 0.003 | 0.000 | 0.006 | 0.003 | 0.019 | 0.000 | 0.010 | 0.003 | 0.045 | 0.019 | 0.003 | 0.010 | 0.006 | 0.019 | 0.010 | 0.016 | 0.003 |
| 0.023 | 0.033 | 0.011 | 0.005 | 0.004 | 0.005 | 0.003 | 0.000 | 0.004 | 0.006 | 0.000 | 0.006 | 0.130 | 0.038 | 0.000 | 0.020 | 0.003 | 0.005 | 0.124 | 0.007 | 0.017 |
| 0.000 | 0.006 | 0.008 | 0.008 | 0.009 | 0.019 | 0.004 | 0.006 | 0.011 | 0.002 | 0.000 | 0.000 | 0.017 | 0.008 | 0.002 | 0.004 | 0.038 | 0.013 | 0.011 | 0.000 | 0.004 |
| 0.018 | 0.046 | 0.009 | 0.003 | 0.003 | 0.006 | 0.002 | 0.001 | 0.008 | 0.007 | 0.077 | 0.007 | 0.000 | 0.036 | 0.002 | 0.021 | 0.006 | 0.004 | 0.058 | 0.007 | 0.023 |
| 0.024 | 0.011 | 0.018 | 0.003 | 0.013 | 0.014 | 0.002 | 0.003 | 0.002 | 0.002 | 0.023 | 0.008 | 0.051 | 0.000 | 0.001 | 0.029 | 0.009 | 0.003 | 0.035 | 0.004 | 0.103 |
| 0.000 | 0.004 | 0.000 | 0.267 | 0.013 | 0.021 | 0.063 | 0.013 | 0.000 | 0.000 | 0.008 | 0.004 | 0.013 | 0.021 | 0.000 | 0.017 | 0.025 | 0.029 | 0.004 | 0.000 | 0.008 |
| 0.012 | 0.008 | 0.045 | 0.006 | 0.006 | 0.012 | 0.003 | 0.004 | 0.007 | 0.001 | 0.006 | 0.007 | 0.022 | 0.024 | 0.002 | 0.000 | 0.010 | 0.008 | 0.038 | 0.000 | 0.016 |
| 0.003 | 0.000 | 0.006 | 0.004 | 0.010 | 0.059 | 0.003 | 0.010 | 0.005 | 0.000 | 0.006 | 0.018 | 0.013 | 0.008 | 0.000 | 0.015 | 0.000 | 0.021 | 0.011 | 0.000 | 0.008 |
| 0.000 | 0.007 | 0.014 | 0.012 | 0.003 | 0.013 | 0.018 | 0.011 | 0.011 | 0.000 | 0.001 | 0.013 | 0.013 | 0.004 | 0.004 | 0.004 | 0.016 | 0.000 | 0.005 | 0.001 | 0.001 |
| 0.039 | 0.022 | 0.022 | 0.003 | 0.002 | 0.012 | 0.003 | 0.002 | 0.007 | 0.006 | 0.103 | 0.006 | 0.080 | 0.027 | 0.004 | 0.065 | 0.004 | 0.004 | 0.000 | 0.004 | 0.021 |
| 0.011 | 0.213 | 0.011 | 0.000 | 0.004 | 0.007 | 0.004 | 0.000 | 0.011 | 0.028 | 0.014 | 0.004 | 0.092 | 0.025 | 0.004 | 0.007 | 0.007 | 0.007 | 0.032 | 0.000 | 0.011 |
| 0.019 | 0.009 | 0.015 | 0.003 | 0.013 | 0.011 | 0.003 | 0.003 | 0.001 | 0.005 | 0.028 | 0.005 | 0.047 | 0.163 | 0.003 | 0.028 | 0.011 | 0.003 | 0.028 | 0.003 | 0.000 |
| 0.004 | 0.008 | 0.008 | 0.124 | 0.004 | 0.012 | 0.028 | 0.080 | 0.012 | 0.012 | 0.004 | 0.008 | 0.004 | 0.004 | 0.072 | 0.008 | 0.016 | 0.032 | 0.004 | 0.000 | 0.000 |
| 0.007 | 0.007 | 0.025 | 0.005 | 0.070 | 0.022 | 0.001 | 0.006 | 0.005 | 0.000 | 0.002 | 0.004 | 0.019 | 0.041 | 0.002 | 0.041 | 0.015 | 0.007 | 0.007 | 0.002 | 0.023 |
| 0.006 | 0.007 | 0.018 | 0.010 | 0.009 | 0.025 | 0.006 | 0.009 | 0.009 | 0.003 | 0.005 | 0.045 | 0.016 | 0.021 | 0.005 | 0.019 | 0.092 | 0.018 | 0.011 | 0.002 | 0.012 |
| 0.000 | 0.008 | 0.005 | 0.008 | 0.003 | 0.026 | 0.033 | 0.005 | 0.036 | 0.003 | 0.013 | 0.036 | 0.013 | 0.008 | 0.005 | 0.010 | 0.018 | 0.054 | 0.005 | 0.000 | 0.003 |
| 0.005 | 0.085 | 0.011 | 0.011 | 0.000 | 0.000 | 0.000 | 0.000 | 0.011 | 0.117 | 0.000 | 0.005 | 0.160 | 0.011 | 0.005 | 0.011 | 0.011 | 0.005 | 0.021 | 0.005 | 0.005 |
| 0.067 | 0.018 | 0.014 | 0.003 | 0.009 | 0.016 | 0.003 | 0.004 | 0.008 | 0.007 | 0.019 | 0.009 | 0.041 | 0.119 | 0.003 | 0.030 | 0.009 | 0.005 | 0.052 | 0.008 | 0.025 |
| 0.007 | 0.010 | 0.019 | 0.012 | 0.002 | 0.020 | 0.037 | 0.006 | 0.012 | 0.001 | 0.003 | 0.006 | 0.019 | 0.010 | 0.006 | 0.014 | 0.021 | 0.197 | 0.008 | 0.001 | 0.008 |
| 0.032 | 0.002 | 0.015 | 0.000 | 0.006 | 0.004 | 0.000 | 0.002 | 0.000 | 0.000 | 0.006 | 0.000 | 0.015 | 0.034 | 0.000 | 0.211 | 0.013 | 0.002 | 0.060 | 0.000 | 0.023 |
| 0.008 | 0.009 | 0.057 | 0.122 | 0.013 | 0.026 | 0.009 | 0.003 | 0.007 | 0.003 | 0.003 | 0.015 | 0.019 | 0.016 | 0.009 | 0.022 | 0.014 | 0.014 | 0.009 | 0.002 | 0.005 |
| 0.008 | 0.000 | 0.012 | 0.004 | 0.012 | 0.016 | 0.049 | 0.025 | 0.021 | 0.012 | 0.008 | 0.021 | 0.008 | 0.012 | 0.000 | 0.004 | 0.025 | 0.041 | 0.000 | 0.000 | 0.000 |

**Figure 2.11 Continued**

| SD | TN | TX | UT | VT | VA | WA | WV | WI | WY |
|---|---|---|---|---|---|---|---|---|---|
| 0.001 | 0.074 | 0.078 | 0.004 | 0.000 | 0.023 | 0.009 | 0.009 | 0.004 | 0.001 |
| 0.007 | 0.003 | 0.092 | 0.044 | 0.003 | 0.011 | 0.038 | 0.003 | 0.011 | 0.008 |
| 0.004 | 0.065 | 0.163 | 0.001 | 0.000 | 0.009 | 0.013 | 0.001 | 0.009 | 0.005 |
| 0.004 | 0.010 | 0.085 | 0.035 | 0.003 | 0.017 | 0.095 | 0.004 | 0.010 | 0.007 |
| 0.010 | 0.016 | 0.079 | 0.027 | 0.007 | 0.011 | 0.039 | 0.007 | 0.008 | 0.032 |
| 0.000 | 0.009 | 0.026 | 0.002 | 0.025 | 0.035 | 0.011 | 0.007 | 0.006 | 0.003 |
| 0.000 | 0.006 | 0.033 | 0.000 | 0.000 | 0.044 | 0.011 | 0.017 | 0.006 | 0.000 |
| 0.002 | 0.041 | 0.067 | 0.004 | 0.002 | 0.038 | 0.011 | 0.008 | 0.009 | 0.002 |
| 0.001 | 0.084 | 0.066 | 0.002 | 0.002 | 0.039 | 0.014 | 0.002 | 0.006 | 0.002 |
| 0.005 | 0.002 | 0.041 | 0.178 | 0.002 | 0.016 | 0.206 | 0.000 | 0.007 | 0.030 |
| 0.002 | 0.033 | 0.065 | 0.004 | 0.000 | 0.010 | 0.015 | 0.007 | 0.086 | 0.003 |
| 0.001 | 0.046 | 0.060 | 0.000 | 0.000 | 0.011 | 0.013 | 0.005 | 0.026 | 0.002 |
| 0.036 | 0.011 | 0.051 | 0.008 | 0.000 | 0.001 | 0.029 | 0.000 | 0.045 | 0.004 |
| 0.004 | 0.011 | 0.102 | 0.007 | 0.000 | 0.016 | 0.021 | 0.000 | 0.006 | 0.009 |
| 0.005 | 0.081 | 0.048 | 0.002 | 0.000 | 0.028 | 0.007 | 0.020 | 0.009 | 0.000 |
| 0.001 | 0.019 | 0.245 | 0.007 | 0.000 | 0.021 | 0.023 | 0.004 | 0.012 | 0.000 |
| 0.000 | 0.006 | 0.051 | 0.006 | 0.022 | 0.064 | 0.010 | 0.006 | 0.003 | 0.003 |
| 0.001 | 0.019 | 0.042 | 0.006 | 0.003 | 0.131 | 0.013 | 0.050 | 0.005 | 0.002 |
| 0.001 | 0.007 | 0.033 | 0.003 | 0.032 | 0.028 | 0.013 | 0.002 | 0.006 | 0.001 |
| 0.003 | 0.037 | 0.062 | 0.005 | 0.000 | 0.024 | 0.018 | 0.006 | 0.034 | 0.001 |
| 0.042 | 0.007 | 0.045 | 0.009 | 0.000 | 0.011 | 0.039 | 0.003 | 0.138 | 0.008 |
| 0.003 | 0.113 | 0.096 | 0.001 | 0.001 | 0.025 | 0.007 | 0.001 | 0.029 | 0.001 |
| 0.004 | 0.025 | 0.083 | 0.005 | 0.005 | 0.011 | 0.020 | 0.003 | 0.014 | 0.003 |
| 0.020 | 0.007 | 0.050 | 0.040 | 0.000 | 0.007 | 0.152 | 0.000 | 0.010 | 0.056 |
| 0.026 | 0.002 | 0.076 | 0.002 | 0.000 | 0.013 | 0.035 | 0.004 | 0.017 | 0.026 |
| 0.003 | 0.003 | 0.048 | 0.065 | 0.000 | 0.008 | 0.060 | 0.003 | 0.000 | 0.003 |
| 0.003 | 0.013 | 0.010 | 0.003 | 0.080 | 0.029 | 0.016 | 0.000 | 0.000 | 0.003 |
| 0.001 | 0.007 | 0.019 | 0.003 | 0.008 | 0.038 | 0.009 | 0.009 | 0.005 | 0.000 |
| 0.006 | 0.009 | 0.300 | 0.025 | 0.004 | 0.011 | 0.019 | 0.004 | 0.006 | 0.017 |
| 0.001 | 0.007 | 0.044 | 0.004 | 0.010 | 0.034 | 0.010 | 0.003 | 0.005 | 0.002 |
| 0.002 | 0.039 | 0.054 | 0.007 | 0.004 | 0.099 | 0.009 | 0.014 | 0.008 | 0.001 |
| 0.021 | 0.000 | 0.050 | 0.000 | 0.000 | 0.008 | 0.042 | 0.004 | 0.017 | 0.004 |
| 0.001 | 0.033 | 0.053 | 0.005 | 0.001 | 0.021 | 0.011 | 0.050 | 0.010 | 0.003 |
| 0.003 | 0.021 | 0.263 | 0.006 | 0.000 | 0.013 | 0.024 | 0.000 | 0.011 | 0.005 |
| 0.004 | 0.011 | 0.025 | 0.017 | 0.000 | 0.009 | 0.256 | 0.003 | 0.005 | 0.009 |
| 0.002 | 0.008 | 0.040 | 0.004 | 0.001 | 0.055 | 0.011 | 0.023 | 0.006 | 0.001 |
| 0.000 | 0.004 | 0.028 | 0.011 | 0.007 | 0.043 | 0.018 | 0.000 | 0.004 | 0.007 |
| 0.000 | 0.043 | 0.050 | 0.007 | 0.001 | 0.064 | 0.008 | 0.007 | 0.005 | 0.003 |
| 0.000 | 0.004 | 0.064 | 0.012 | 0.000 | 0.008 | 0.048 | 0.000 | 0.016 | 0.036 |
| 0.001 | 0.000 | 0.070 | 0.002 | 0.000 | 0.040 | 0.013 | 0.005 | 0.007 | 0.001 |
| 0.002 | 0.013 | 0.000 | 0.005 | 0.001 | 0.022 | 0.026 | 0.005 | 0.008 | 0.002 |
| 0.003 | 0.013 | 0.064 | 0.000 | 0.003 | 0.013 | 0.046 | 0.003 | 0.008 | 0.028 |
| 0.005 | 0.005 | 0.021 | 0.011 | 0.000 | 0.027 | 0.021 | 0.005 | 0.005 | 0.000 |
| 0.003 | 0.044 | 0.045 | 0.007 | 0.005 | 0.000 | 0.018 | 0.047 | 0.007 | 0.001 |
| 0.003 | 0.010 | 0.048 | 0.031 | 0.001 | 0.021 | 0.000 | 0.001 | 0.005 | 0.006 |
| 0.000 | 0.030 | 0.045 | 0.000 | 0.000 | 0.138 | 0.004 | 0.000 | 0.004 | 0.002 |
| 0.009 | 0.009 | 0.060 | 0.003 | 0.001 | 0.014 | 0.022 | 0.001 | 0.000 | 0.005 |
| 0.029 | 0.004 | 0.070 | 0.091 | 0.000 | 0.008 | 0.041 | 0.000 | 0.008 | 0.000 |

Table 2.1 Summary Statistics

| Full Period (1983-2008) | Benefit and Tax Rate Variables | Obs. | Mean | Std. Dev. |
|---|---|---|---|---|
| | Maximum Benefit for Family of 3 | 1248 | 523.36 | 202.35 |
| | Effective Benefit for Family of 3 | 1248 | 482.65 | 201.72 |
| | Effective Tax Rate on Earned Income | 1248 | 27.23 | 17.03 |
| **AFDC (1983-1991)** | Maximum Benefit for Family of 3 | 432 | 616.55 | 222.69 |
| | Effective Benefit for Family of 3 | 432 | 599.67 | 212.55 |
| | Effective Tax Rate on Earned Income | 432 | 37.58 | 13.23 |
| **Waiver Period (1992-1996)** | Maximum Benefit for Family of 3 | 240 | 528.22 | 184.48 |
| | Effective Benefit for Family of 3 | 240 | 514.09 | 176.2 |
| | Effective Tax Rate on Earned Income | 240 | 34.95 | 12.71 |
| **TANF (1997-2008)** | Maximum Benefit for Family of 3 | 576 | 451.44 | 160.5 |
| | Effective Benefit for Family of 3 | 576 | 381.79 | 143.49 |
| | Effective Tax Rate on Earned Income | 576 | 16.25 | 14.31 |
| | **Additional Welfare Variables** | | | |
| **TANF only (2000-2008)** | % of cases closed by sanction | 432 | 11.13 | 11.51 |
| | % of cases closed by state policy | 432 | 12.78 | 10.53 |
| | Approval rate | 432 | 55.47 | 19.33 |
| | **Control Variables (1983-2008)** | | | |
| **Full Period (1983-2008)** | population in 1000s | 1248 | 3320.21 | 2692.72 |
| | African American proportion of population | 1248 | 9.83 | 9.65 |
| | median wage | 1248 | 16.14 | 1.76 |
| | poverty rate | 1248 | 12.85 | 3.85 |
| | per capita employment | 1248 | 48.04 | 3.59 |
| | female unemployment rate | 1248 | 3.17 | 0.99 |
| | democratic governor | 1248 | 0.5 | 0.5 |

**Table 2.2 Static Panel GMM Estimates of Neighbor's Reaction Function for Alternative Welfare Policy Instruments, full period (1983-2008)**

| Policy Instrument: | **Maximum Benefits** | | **Effective Benefits** | | **ETR on Earned Income** | |
|---|---|---|---|---|---|---|
| $\phi WY_p$ | 0.926** | | 0.745*** | | 0.779*** | |
| | (0.420) | | (0.283) | | (0.241) | |
| $\phi_0 WY_p * (I_{it})$ | | 1.028*** | | 0.843*** | | 0.988*** |
| | | (0.381) | | (0.233) | | (0.288) |
| $\phi_1 WY_p * (1 - I_{it})$ | | 1.014** | | 0.815*** | | 0.666** |
| | | (0.382) | | (0.234) | | (0.275) |
| **Wald-test for Asymmetries** | | 8.12 | | 10.36 | | 11.37 |
| $(\phi_0 = \phi_1)$ p-value | | 0.007 | | 0.002 | | 0.002 |
| Observations | 1248 | 1248 | 1248 | 1248 | 1248 | 1248 |
| AR (1) p-value | 0.402 | 0.376 | 0.172 | 0.112 | 0.002 | 0.0003 |
| AR (2) p-value | 0.769 | 0.420 | 0.045 | 0.048 | 0.947 | 0.466 |
| Hansen's J-statistic | 5.418 | 8.499 | 10.08 | 13.06 | 11.98 | 14.03 |
| p-value | 0.862 | 0.668 | 0.433 | 0.289 | 0.286 | 0.231 |
| No. of instruments | 44 | 46 | 44 | 46 | 44 | 46 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. $\phi WY_p$ denotes policy response to neighbors in model with no asymmetries. For asymmetry model, $\phi_0 WY_p * (I_{it})$ / $\phi_1 WY_p * (1 - I_{it})$ denote responses of states with policy values greater than/less than their neighbor's on average. All spatial variables are instrumented with their second through forth lags collapsed.

**Table 2.3 Static Panel GMM Estimates of Neighbor's Reaction Function for Alternative Welfare Policy Instruments by Welfare Period**

| | **Policy instrument is Maximum Benefit** | | | | | | **Policy instrument is Effective Benefit** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AFDC | | Waiver | | TANF | | AFDC | | Waiver | | TANF | |
| $\phi \mathrm{WY_p}$ | 0.694* | | 0.959*** | | 0.867*** | | 0.853*** | | 0.907*** | | 0.934*** | |
| | (0.358) | | (0.221) | | (0.303) | | (0.266) | | (0.252) | | (0.234) | |
| $\phi_0 \mathrm{WY_p} * (\mathrm{I_{it}})$ | | 0.769** | | 0.934*** | | 1.200*** | | 0.932*** | | 1.059*** | | 0.975*** |
| | | (0.376) | | (0.244) | | (0.241) | | (0.339) | | (0.246) | | (0.158) |
| $\phi_1 \mathrm{WY_p} * (1 - \mathrm{I_{it}})$ | | 0.761** | | 0.905*** | | 1.179*** | | 0.918*** | | 1.038*** | | 0.922*** |
| | | (0.375) | | (0.250) | | (0.238) | | (0.335) | | (0.241) | | (0.163) |
| **Wald-test for Asymmetries** $(\phi_0 = \phi_1)$ | | 1.97 | | 1.89 | | 4.53 | | 3.69 | | 3.82 | | 5.91 |
| p-value | | 0.167 | | 0.175 | | 0.039 | | 0.061 | | 0.057 | | 0.019 |
| Observations. | 432 | 432 | 240 | 240 | 576 | 576 | 432 | 432 | 240 | 240 | 576 | 576 |
| AR(1) p-value | 0.982 | 0.82 | 0.441 | 0.377 | 0.355 | 0.442 | 0.591 | 0.944 | 0.15 | 0.647 | 0.169 | 0.0539 |
| AR(2) p-value | 0.211 | 0.241 | 0.779 | 0.911 | 0.702 | 0.692 | 0.707 | 0.645 | 0.154 | 0.401 | 0.0743 | 0.128 |
| Hansen's J-statistic | 1.927 | 6.178 | 4.335 | 7.137 | 6.736 | 10.28 | 5.354 | 9.877 | 2.928 | 11.35 | 10.84 | 17.36 |
| p-value | 0.997 | 0.939 | 0.931 | 0.895 | 0.75 | 0.671 | 0.866 | 0.704 | 0.983 | 0.582 | 0.37 | 0.183 |
| No. of instruments | 27 | 31 | 23 | 27 | 30 | 34 | 27 | 31 | 23 | 27 | 30 | 34 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. All non-dummy variables are in logs. $\phi WY_p$ denotes policy response to neighbors in model with no asymmetries. For the asymmetry model, $\phi_0 \mathrm{WY_p} * (\mathrm{I_{it}})$ / $\phi_1 \mathrm{WY_p} * (1 - \mathrm{I_{it}})$ denote responses of states with policy values greater than/less than their neighbor's on average.

**Table 2.4 Static Panel GMM Estimates of Neighbor's Reaction Function for Alternative Welfare Policy Instruments by Welfare Period**

| | Policy instrument is ETR on earned income | | | | | |
|---|---|---|---|---|---|---|
| | AFDC | | Waiver | | TANF | |
| $\phi WY_p$ | 0.843*** | | 0.486 | | 0.624*** | |
| | (0.266) | | (0.614) | | (0.214) | |
| $\phi_0 WY_p * (I_{it})$ | | 0.923*** | | 0.882* | | 0.906*** |
| | | (0.261) | | (0.485) | | (0.178) |
| $\phi_1 WY_p * (1 - I_{it})$ | | 0.833*** | | 0.776* | | 0.459** |
| | | (0.247) | | (0.452) | | (0.215) |
| **Wald-test for Asymmetries** | | 2.58 | | 2.12 | | 11.92 |
| $(\phi_0 = \phi_1)$ p-value | | 0.115 | | 0.15 | | 0.001 |
| Observations. | 432 | 432 | 240 | 240 | 576 | 576 |
| AR(1) p-value | 0.001 | 0.021 | 0.149 | 0.175 | 0.005 | 0.002 |
| AR(2) p-value | 0.036 | 0.010 | 0.202 | 0.270 | 0.850 | 0.872 |
| Hansen's J-statistic | 6.216 | 14.25 | 6.376 | 9.642 | 8.150 | 11.22 |
| p-value | 0.797 | 0.356 | 0.783 | 0.723 | 0.614 | 0.592 |
| No. of instruments | 27 | 31 | 23 | 27 | 30 | 34 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. $\phi WY_p$ denotes policy response to neighbors in model with no asymmetries. For asymmetry model, $\phi_0 WY_p * (I_{it}) / \phi_1 WY_p * (1 - I_{it})$ denote responses of states with policy values greater than/less than their neighbor's on average. All spatial variables are instrumented with their second through forth lags collapsed

**Table 2.5 Static Panel GMM Estimates for Neighbor's Reaction Function for Additional Welfare Policy Instruments, TANF only (2000-2008)**

| | Approval Rate | | Sanction Use | | Non-Sanction State Policy | |
|---|---|---|---|---|---|---|
| $\phi WY_p$ | 0.765* | | 0.202 | | 0.254 | |
| | (0.464) | | (0.466) | | (0.320) | |
| $\phi_0 WY_p * (I_{it})$ | | 0.940** | | 1.161*** | | 0.578* |
| | | (0.371) | | (0.288) | | (0.333) |
| $\phi_1 WY_p * (1 - I_{it})$ | | 1.916*** | | -0.277 | | 0.111 |
| | | (0.672) | | (0.346) | | (0.334) |
| **Wald-test for Asymmetries** | | 5.89 | | 24.18 | | 7.32 |
| $(\phi_0 = \phi_1)$ p-value | | 0.01 | | 0.00 | | 0.009 |
| Observations | 432 | 432 | 432 | 432 | 432 | 432 |
| AR (1) p-value | 0.712 | 0.101 | 0.0139 | 0.00336 | 0.143 | 0.0167 |
| AR (2) p-value | 0.171 | 0.814 | 0.568 | 0.448 | 0.298 | 0.424 |
| Hansen's J-statistic | 5.308 | 11.66 | 14.15 | 13.64 | 5.434 | 9.920 |
| p-value | 0.870 | 0.556 | 0.166 | 0.399 | 0.860 | 0.700 |
| No. of instruments | 27 | 31 | 27 | 31 | 27 | 31 |

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All non-dummy variables are in logs. $\phi WY_p$ denotes policy response to neighbors in model with no asymmetries. For asymmetry model, $\phi_0 WY_p * (I_{it})$ / $\phi_1 WY_p * (1 - I_{it})$ denote responses of states with policy values greater than/less than their neighbor's on average. All spatial variables are instrumented with their second through forth lags collapsed

**Table 2.6 Dynamic Panel GMM Estimates of Neighbor's Reaction Function for Alternative Welfare Policy Instruments, full period (1983-2008)**

| Policy Instrument: | Maximum Benefits | | Effective Benefits | | ETR on Earned Income | |
|---|---|---|---|---|---|---|
| $\phi WY_p$ | 0.095 | | 0.234** | | 0.320** | |
| | (0.107) | | (0.116) | | (0.161) | |
| $\phi_0 WY_p * (I_{it})$ | | 0.040 | | 0.275* | | 0.442* |
| | | (0.089) | | (0.163) | | (0.249) |
| $\phi_1 WY_p * (1 - I_{it})$ | | 0.044 | | 0.249 | | 0.365* |
| | | (0.088) | | (0.163) | | (0.213) |
| $\gamma Y_{p,t-1}$ | 0.857*** | 0.902*** | 0.699*** | 0.506*** | 0.486*** | 0.438*** |
| | (0.094) | (0.088) | (0.095) | (0.123) | (0.106) | (0.157) |
| **Long Run Coefficients** | | | | | | |
| $\phi/(1-\gamma)$ or $\phi_0/(1-\gamma)$ | 0.667 | 0.406 | .777*** | 0.557** | .622** | .787*** |
| | (0.574) | (.730) | (0.285) | (0.282) | (0..296) | (0.312) |
| $\phi_1 \ /(1-\gamma)$ | | 0.447 | | 0.504* | | 0.649* |
| | | (.713) | | (0.286) | | (0.346) |
| **Wald-test for Asymmetries** | | 1.42 | | 15.28 | | 0.33 |
| $(\phi_0 = \phi_1)$ p-value | | 0.234 | | 0.000 | | 0.567 |
| AR (2) p-value | 0.389 | .234 | 0.780 | 0.788 | 0.208 | 0.241 |
| Observations | 1200 | 1200 | 1200 | 1200 | 1200 | 1200 |
| Hansen's J-statistic | 9.198 | 7.984 | 6.176 | 6.492 | 9.301 | 17.54 |
| p-value | 0.604 | 0.786 | 0.861 | 0.889 | 0.594 | 0.130 |
| No. of instruments | 45 | 47 | 45 | 47 | 45 | 47 |

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All non-dummy variables are in logs. Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

**Table 2.7 Dynamic Panel GMM Estimates of Neighbor's Reaction Function for Alternative Welfare Policy Instruments by Welfare Period**

| | Policy instrument is maximum benefit | | | | | | Policy instrument is effective benefit | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AFDC | | Waiver | | TANF | | AFDC | | Waiver | | TANF | |
| $\phi WY_p$ | 0.181 | | 0.114 | | 0.129 | | 0.118 | | 0.189 | | 0.331** | |
| | (0.137) | | (0.126) | | (0.086) | | (0.127) | | (0.157) | | (0.162) | |
| $\phi_0 WY_p * (I_{it})$ | | 0.162 | | 0.136 | | 0.153* | | 0.178 | | 0.130 | | 0.330** |
| | | (0.160) | | (0.172) | | (0.089) | | (0.161) | | (0.159) | | (0.159) |
| $\phi_1 WY_p * (1 - I_{it})$ | | 0.163 | | 0.135 | | 0.151* | | 0.175 | | 0.125 | | 0.301* |
| | | (0.155) | | (0.173) | | (0.088) | | (0.157) | | (0.160) | | (0.156) |
| $\gamma Y_{p,t-1}$ | 0.768*** | 0.763*** | 0.884*** | 0.844*** | 0.940*** | 0.919*** | 0.795*** | 0.705*** | 0.786*** | 0.837*** | 0.746*** | 0.595*** |
| | (0.117) | (0.170) | (0.116) | (0.142) | (0.050) | (0.043) | (0.252) | (0.265) | (0.128) | (0.130) | (0.121) | (0.159) |
| **Long Run Coefficients** | | | | | | | | | | | | |
| $\phi/(1-\gamma)$ or $\phi_1/(1-\gamma)$ | 0.780 | 0.681* | .983*** | .876** | 2.155 | 1.890* | 0.579 | 0.602 | 0.873** | .799* | 1.303*** | .817*** |
| | (0.538) | (0.385) | (0.385) | (0.453) | (1.674) | (1.119) | (0.759) | (0. 400) | (0.457) | (0.474) | (0.386) | (0.268) |
| $\phi_1/(1-\gamma)$ | | 0.687* | | .870* | | 1.860* | | 0.594 | | 0.77 | | .744*** |
| | | (0.37) | | (0.47) | | (1.10) | | (0.40) | | (0.49) | | (0.28) |
| **Wald-test for Asymmetries** $(\phi_0 = \phi_1)$ | | 0.04 | | 0.02 | | 0.61 | | 4.1 | | 2.14 | | 4.16 |
| p-value | | 0.848 | | 0.879 | | 0.435 | | 0.043 | | 0.143 | | 0.0414 |
| Observations | 384 | 384 | 240 | 240 | 576 | 576 | 384 | 384 | 240 | 240 | 576 | 576 |
| AR (2) p-value | 0.431 | 0.455 | 0.344 | 0.418 | 0.933 | 0.987 | 0.836 | 0.813 | 0.818 | 0.634 | 0.75 | 0.8 |
| Hansen's J-statistic | 15.25 | 17.62 | 11.72 | 16.18 | 16.18 | 16.67 | 14.96 | 16.84 | 17.35 | 19.12 | 24.18 | 27.35 |
| p-value | 0.645 | 0.673 | 0.861 | 0.759 | 0.58 | 0.731 | 0.184 | 0.265 | 0.5 | 0.577 | 0.149 | 0.16 |
| No. of instruments | 35 | 39 | 31 | 35 | 39 | 43 | 28 | 32 | 31 | 35 | 39 | 43 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

**Table 2.8 Dynamic Panel Estimation Results for the Effective Tax Rate by Welfare Period**

| | Policy instrument is ETR on earned Income | | | | | |
|---|---|---|---|---|---|---|
| | AFDC | | Waiver | | TANF | |
| $\phi WY_p$ | 0.593** | | 0.167 | | 0.118 | |
| | (0.258) | | (0.425) | | (0.167) | |
| $\phi_0 WY_p * (I_{it})$ | | 0.545** | | 0.402 | | 0.479** |
| | | (0.225) | | (0.307) | | (0.233) |
| $\phi_1 WY_p * (1 - I_{it})$ | | 0.472** | | 0.333 | | 0.138 |
| | | (0.227) | | (0.303) | | (0.211) |
| $\gamma Y_{p,t-1}$ | -0.186 | -0.036 | 0.740*** | 0.457* | 0.808*** | 0.445*** |
| | (0.179) | (0.088) | (0.276) | (0.241) | (0.265) | (0.134) |
| **Long Run Coefficients** | | | | | | |
| $\phi/(1-\gamma)$ or $\phi_0/(1-\gamma)$ | 0.450** | .526** | .640 | .740 | .617 | .863*** |
| | (0.251) | (0.224) | (1.687) | (.672) | (.606) | (0.341) |
| $\phi_1/(1-\gamma)$ | | 0.456** | | .613 | | 0.248 |
| | | (0.225) | | (.637) | | (0.361) |
| **Wald-test for Asymmetries** | | 6.08 | | 2.04 | | 6.91 |
| $(\phi_0 = \phi_1)$ p-value | | 0.014 | | 0.15 | | 0.009 |
| Observations | 384 | 384 | 240 | 240 | 576 | 576 |
| AR (2) p-value | 0.040 | 0.063 | 0.158 | 0.223 | 0.413 | 0.471 |
| Hansen's J-statistic | 12.20 | 18.39 | 12.36 | 19.70 | 12.74 | 28.65 |
| p-value | 0.837 | 0.624 | 0.828 | 0.540 | 0.311 | 0.123 |
| No. of instruments | 35 | 39 | 31 | 35 | 32 | 43 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs.
Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

**Table 2.9 Dynamic Panel GMM Estimates of Neighbor's Reaction Function for the Approval Rate, Sanction Use, and Non-sanction State Policy, TANF only (2000-2008)**

| | Approval Rate | | Sanction Use | | Non-Sanction State Policy | |
|---|---|---|---|---|---|---|
| $\phi W Y_p$ | 0.034 | | 0.168 | | 0.009 | |
| | (0.135) | | (0.294) | | (0.165) | |
| $\phi_0 W Y_p * (I_{it})$ | | 0.121 | | 0.596* | | 0.495* |
| | | (0.160) | | (0.308) | | (0.266) |
| $\phi_1 W Y_p * (1 - I_{it})$ | | 0.298 | | -0.011 | | -0.055 |
| | | (0.229) | | (0.217) | | (0.277) |
| $\gamma Y_{t-1,p}$ | 0.832*** | 0.722*** | 0.823*** | 0.676*** | 0.254 | 0.115 |
| | (0.075) | (0.119) | (0.187) | (0.160) | (0.258) | (0.273) |
| **Long Run Coefficients** | | | | | | |
| $\phi/(1-\gamma)$ or $\phi_0/(1-\gamma)$ | .200 | 0.434 | .949 | 1.842* | 0.012 | 0.559* |
| | (.818) | (0.629) | (1.927) | (.984) | (0..222) | (0.304) |
| or $\phi_1/(1-\gamma)$ | | 1.072 | | -0.033 | | -0.062 |
| | | (0.833) | | (.669) | | (0313) |
| **Wald-test for asymmetries** | | 2.24 | | 5.53 | | 6.90 |
| $(\phi_0 = \phi_1)$ p-value | | 0.141 | | .023 | | 0.012 |
| Observations | 336 | 336 | 336 | 336 | 336 | 336 |
| AR (2) p-value | 0.116 | 0.0805 | 0.448 | 0.754 | 0.266 | 0.616 |
| Hansen's J-statistic | 14.05 | 14.04 | 19.83 | 26.20 | 20.23 | 27.16 |
| p-value | 0.781 | 0.900 | 0.405 | 0.243 | 0.381 | 0.205 |
| No. of instruments | 35 | 39 | 35 | 39 | 35 | 39 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

**Table 2.10 Sensitivity Analysis: Alternative Weight Matrix Specifications for the Static and Dynamic Models**

**Static Models**

| | Contiguity Weights | | | | Unrestricted Distance | | | |
|---|---|---|---|---|---|---|---|---|
| Weight Matrix | $W^{Baseline}$ | $W^{Mig}$ | $W^{Pov\_Mig}$ | $W^{Edu\_Mig}$ | $W^{Dist}$ | $W^{Mig}$ | $W^{Pov\_Mig}$ | $W^{Edu\_Mig}$ |
| **Maximum Benefit:** | | | | | | | | |
| $\phi$WY | 0.926** | 0.858* | 0.862* | 0.809 | 0.739 | -0.035 | -0.191 | -0.362 |
| | (0.420) | (0.462) | (0.455) | (0.505) | (0.531) | (0.940) | (1.013) | (0.848) |
| **Effective Benefit** | | | | | | | | |
| $\phi$WY | 0.745** | 0.608* | 0.542 | 0.637* | 0.541 | 0.119 | -0.004 | -0.278 |
| | (0.290) | (0.323) | (0.326) | (0.352) | (0.421) | (0.977) | (1.016) | (0.731) |
| **Effective tax rate:** | | | | | | | | |
| $\phi$WY | 0.779*** | 0.496* | 0.476* | 0.515* | .790* | 0.798 | 0.562 | 0.546 |
| | (0.241) | (0.258) | (0.264) | (0.262) | (0.436) | (0.549) | (0.572) | (0.530) |

**Dynamic Models**

| | Contiguity Weights | | | | Unrestricted Distance | | | |
|---|---|---|---|---|---|---|---|---|
| | $W^{Baseline}$ | $W^{Mig}$ | $W^{Pov\_Mig}$ | $W^{Edu\_Mig}$ | $W^{Dist}$ | $W^{Mig}$ | $W^{Pov\_Mig}$ | $W^{Edu\_Mig}$ |
| **Maximum Benefit:** | | | | | | | | |
| $\phi$WY | 0.095 | 0.022 | 0.035 | 0.006 | 0.179* | -0.114 | -0.095 | -0.090 |
| | (0.107) | (0.117) | (0.126) | (0.122) | (0.101) | (0.188) | (0.186) | (0.152) |
| **Effective Benefit:** | | | | | | | | |
| $\phi$WY | 0.234** | 0.199 | 0.230* | 0.195 | -0.017 | -0.215 | -0.205 | -0.174 |
| | (0.116) | (0.132) | (0.126) | (0.137) | (0.199) | (0.223) | (0.215) | (0.162) |
| **Effective tax rate:** | | | | | | | | |
| $\phi$WY | .320** | 0.305* | 0.339* | 0.312* | 0.770** | 0.761 | 0.791* | 0.722 |
| | (0.161) | (0.179) | (0.183) | (0.175) | (0.303) | (0.476) | (0.476) | (0.465) |

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All non-dummy variables are in logs. Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

**Table 2.11 Sensitivity Analysis: Allowing for Lagged Policy Responses in Static Model**

| Policy Instrument | Maximum Benefit | | Effective Benefit | | Effective Tax Rate | |
|---|---|---|---|---|---|---|
| Lag | lag 0 | lag 1 | lag 0 | lag 1 | lag 0 | lag 1 |
| $\phi$WY | 0.926** | 0.752** | 0.745** | 0.709 | 0.779*** | 0.767* |
| | (0.420) | (0.329) | (0.290) | (0.525) | (0.241) | (0.386) |
| Observations | 1248 | 1200 | 1248 | 1200 | 1248 | 1200 |
| AR(1) p-value | 0.402 | 0.683 | 0.172 | 0.204 | 0.002 | 0.002 |
| AR(2) p-value | 0.769 | 0.378 | 0.0450 | 0.155 | 0.947 | 0.702 |
| Hansen's J- test | 5.418 | 5.385 | 10.08 | 10.88 | 11.98 | 12.85 |
| p-value | 0.862 | 0.864 | 0.433 | 0.367 | 0.286 | 0.232 |
| No. of instruments | 44 | 43 | 44 | 43 | 44 | 43 |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

**Table 2.12 Sensitivity Analysis: Allowing for Lagged Policy Responses in Dynamic Model**

| | Maximum Benefit | | | Effective Benefit | | | Effective Tax Rate | | |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | lag 0 | lag 1 | lag 0&1 | lag 0 | lag 1 | lag 0&1 | lag 0 | lag 1 | lag 0&1 |
| $\phi_0 WY_t$ | 0.095 | | 0.357 | 0.234** | | 0.682** | 0.320** | | 0.262 |
| | (0.107) | | (0.415) | (0.116) | | (0.321) | (0.161) | | (0.299) |
| $\phi_1 WY_{t-1}$ | | 0.071 | -0.246 | | 0.310** | -0.264 | | 0.343** | 0.033 |
| | | (0.077) | (0.355) | | (0.138) | (0.198) | | (0.154) | (0.243) |
| $\gamma Y_{t-1,p}$ | 0.857*** | 0.906*** | 0.885*** | 0.699*** | 0.631*** | 0.613*** | 0.486*** | 0.527*** | 0.511*** |
| | (0.094) | (0.083) | (0.092) | (0.095) | (0.094) | (0.122) | (0.106) | (0.099) | (0.113) |
| Long Run Coefficients | | | | | | | | | |
| $\phi_0 + \phi_1/(1-\gamma)$ | 0.67 | 0.75 | 0.96 | .777*** | 0.841*** | 1.078*** | 0.622** | 0.726** | 0.603** |
| | (0.574) | (0.626) | (0.918) | (0.285) | (0.317) | (0.253) | (0.296) | (0.345) | (0.287) |
| Observations | 1200 | 1152 | 1152 | 1200 | 1152 | 1152 | 1200 | 1152 | 1152 |
| AR(1) p-value | 0.00 | 0.00 | 0.00 | 0.13 | 0.15 | 0.13 | 0.00 | 0.00 | 0.00 |
| AR(2) p-value | 0.389 | 0.437 | 0.230 | 0.780 | 0.738 | 0.926 | 0.208 | 0.224 | 0.208 |
| Hansen's J- test | 8.204 | 12.61 | 9.909 | 3.109 | 4.353 | 5.158 | 9.301 | 8.673 | 9.548 |
| p-value | 0.695 | 0.319 | 0.624 | 0.989 | 0.958 | 0.952 | 0.594 | 0.652 | 0.656 |
| No. of instruments | 45 | 44 | 46 | 45 | 44 | 46 | 45 | 44 | 46 |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All non-dummy variables are in logs. Spatial variables and lagged dependent variable are instrumented with their collapsed lags.

## 3 The Elasticity of Taxable Income: Sensitivity to Key Economic and Statistical Decisions

### 3.1 Introduction

Understanding how taxable income responds to marginal tax rates, i.e. the elasticity of taxable income (ETI), has become a focal outcome for research and policy on the optimal design of the income tax and transfer system (Feldstein (1995); Auten and Carroll (1999); Gruber and Saez (2002); Kopczuk (2005), Kopczuk (2012); Heim (2009); Blomquist and Selin (2010); Giertz (2010); Saez (2001); Brewer *et al.* (2010); Saez *et al.* (2012), Kleven and Schultz (2012)). This interest stems in part from the fact that under certain assumptions the ETI can serve as a sufficient statistic for optimal tax analysis Saez *et al.* (2012). That is, conditional on the shape of the income distribution, how income changes with changes in the marginal tax rate determines the revenue-maximizing rate of taxation for high earnersthat tax rate where revenue is likely to fall with incremental increases in the marginal tax rate. Using the Saez, et al. formula, Keane (2011), Table 1) shows that the top marginal rate can be as high as 100 percent when the elasticity is 0, and that it falls quickly as the elasticity increases. For example, under plausible redistributive preferences, the top tax rate falls to about fifty percent with an elasticity of 0.5. This suggests that whether it is a sufficient statistic or not, pinning down the ETI has important ramifications for the progressivity of the tax system.

I present new evidence on the elasticity of taxable income, with particular emphasis on how the ETI varies with key economic and statistical decisions such as measurement of the tax rate, heterogeneity across education attainment, selection on observables and unobservables, and identification. I begin with the canonical ETI specification and identification scheme that regresses the change in log annual income on the change in the log net-of-tax share, defined as one minus the marginal tax rate, conditional on initial log income to control for possible regression-to-the-mean effects. Because the change in log net-of-tax is likely endogenous, most authors have adopted some variant of the identification scheme proposed by Gruber and Saez (2002) whereby the net-of-tax share is instrumented with the predicted change in log net-of-tax share that would obtain if incomes grew from one year to the next solely due to inflation.

The first point of departure with the prior literature is the use of two-year matched panels from the Current Population Survey (CPS).[1] With few exceptions (e.g. Moffitt and Wilhelm (2000)), the ETI literature uses some variant of taxpayer panel data. The advantage of tax panels over the CPS is the quality of data for measuring deductions and exemptions necessary to move from gross income to taxable income, coupled with the fact that most tax panels follow the same person for several years whereas the maximum panel length in the CPS is two years. However, this is weighed against limitations of tax data such as the fact that it is often not publically available, it has limited demographic information, and it does not necessarily capture the low end of the distribution because many poor have frequent non-filing episodes. Even with the possible shortcomings in the measurement of deductions and exemptions in the CPS, I obtain baseline estimates of the ETI of 0.22 for gross income and 0.27 for taxable income, which are remarkably close to the midpoint estimate of 0.25 from taxpayer panels as reported in Saez *et al.* (2012).

This baseline estimate, however, is cut in half by including the FICA payroll tax in the definition of net of tax share. Although the tax reforms of the 1980s removed several million households from the federal tax rolls, substantial expansions in the payroll tax base caused a shift in tax burdens from income to payroll. The fraction of families with relatively higher payroll tax burdens increased from forty-four percent in 1979 to nearly sixty-seven percent in 1999 (Mitrusi and Poterba (2000)). Perhaps surprising, with the exception of Heim (2009), the ETI literature using U.S. data has not explored the effects of payroll taxes on the estimated elasticity. The finding of a dampened response with FICA included

[1] To my knowledge I am the first to use matched CPS panels to estimate the ETI. Singleton (2011) uses a cross section of the CPS linked to administrative wage data from the IRSs Detailed Earnings. He attempts to identify the ETI through the marriage penalty relief provision contained in the 2001 Economic Growth and Tax Relief Reconciliation Act.

likely results from the payroll tax flattening the combined marginal tax rate schedule across workers over time.

I next exploit the key advantage of the CPS over tax panels, which is the availability of extensive demographic information. A common finding is that the ETI increases as one moves up the income distribution, suggesting that it is high income taxpayers driving the response. A concern raised in the literature, however, is that these estimates may be affected by mean reversion, and thus may not capture more permanent responses to tax changes. Alternatively, education attainment is well known in the labor supply and consumption literatures to be a good proxy for permanent income (Blundell and MaCurdy (1999); Attanasio and Weber (2010)) and thus variation in the ETI by education attainment is less likely to reflect mean reversion. I find a strong positive gradient in the ETI with respect to educationthe ETI for a post-graduate is two-three times larger than a college graduate – suggesting that identification of the ETI is driven by the highly skilled, i.e. those with permanently higher incomes.

Another advantage of the demographic information in the CPS is it permits us to more comprehensively examine how selection on observables and unobservables may affect the ETI. Controlling for the influence of nonrandom selection into the labor market has been a focal interest in the labor supply literature (Heckman (1979); Mroz (1987); Blundell and MaCurdy (1999)), but has not received similar attention in the ETI literature. In ETI papers it is standard to truncate low-income families from the sample, e.g. with incomes below \$20,000 in Auten and Carroll (1999), or \$10,000 in Gruber and Saez (2002), under the assumption that this truncation is likely to impart little bias in the ETI. While some authors have examined how the elasticity changes when the truncation point changes, selection has not been modeled formally. I examine how the ETI changes with controls for selection on observables (i.e. expanded demographic controls) as well as on unobservables (i.e. a Heckman (1979) type selection correction). I find that controlling for selection reduces the ETI by about one-third. What matters though is whether one controls for selection, and not the form of selection. That is, whether I just include observed demographics, or model formally selection on unobservables, the ETI falls by a similar amount.

I then turn to identification of the ETI via instrument selection. The canonical instrument using the predicted (or synthetic) net-of-tax share differs from approaches commonly found in the labor supply and taxation literature, which tends to either exploit the nonlinearity of the tax code, socioeconomic exclusion restrictions in the first stage, or time-series restrictions on the model control variables and error term (Hausman (1981); MaCurdy *et al.* (1990); Blundell *et al.* (1998); Ziliak and Kniesner (1999), Ziliak and Kniesner (2005); Moffitt and Wilhelm (2000); Keane (2011)). Some have raised concerns about the standard identification in ETI models (Moffitt and Wilhelm (2000); Blomquist and Selin (2010); Weber (2011)). Because the CPS is primarily employed as a repeated cross-section, I examine the robustness of the ETI by adopting a Wald-type grouping instrumental variables estimator akin to that found in Blundell *et al.* (1998). Specifically, I construct a series of birth-year by education cohorts and impose the identification restriction that tax reforms of the past several decades are sufficient to cause changes in the net-of-tax share to vary differentially over a fixed cohort effect, a fixed time effect, and nonrandom changes in the composition of the labor force. Here, identification breaks down in that the ETI estimates are negative, unless I drop controls for time. This inconsistency with theory does not occur when I estimate a parallel model for hours of work as a function of after-tax wages and virtual incomes, suggesting that technological change and other factors affecting the pre-tax wage structure differentially across cohorts provide an important source of variation not present in the standard ETI framework. I conclude with a model that combines insights from the canonical ETI framework with those from the grouping estimator for a plausibly more exogenous instrument that yields larger elasticities in the range of 0.4-0.5.

## 3.2 Estimation and Identification of the Elasticity of Taxable Income

The canonical approach to estimating the effect of taxation on labor supply is to assume that a taxpayer maximizes a utility function over a composite consumption good $c$ and hours of work $h$, $U(c,h)$, subject to a budget constraint of $c = wh + V + NT(wh + N)$, where $V$ is nontaxable nonlabor income, $N$ is taxable nonlabor income, $w$ is the pre-tax hourly wage rate, $T(\cdot)$ is the tax function, and the price of consumption has been normalized to 1. Solving the optimization problem results in an optimal hours of work function of $h(w(1-\tau), N^v)$, where $\tau$ is the marginal tax rate and $N^v$ is virtual nonlabor income $N + V + \tau whT(\cdot)$, which is that level of compensation needed to make the worker behave as if they faced a constant marginal tax rate on all taxable income. In this framework, both the after-tax wage and virtual nonlabor income are treated as endogenous in estimation since the tax rate an individual faces is an implicit function of hours of work. Feldstein (1995) argued that this approach missed other behavioral responses to tax law changes such as shifting compensation from taxable to nontaxable income, or changes in the timing of compensation. Instead, he posited that workers preferences were over consumption and an income supply function, $y$, $U(c,y)$, and solving the revised optimization problem resulted in an income supply function of $y(1-\tau, N^v)$ that depends on the net-of-tax share $(1-\tau)$ and virtual nonlabor income. Like the labor supply predecessor, both the net-of-tax share and virtual incomes are treated as endogenous in estimation.

Gruber and Saez (2002) extended the Feldstein approach by motivating the income supply model within the context of the Slutsky equation in elasticity form, which relates how income supply responds to infinitesimal changes in net-of-tax shares and captures both substitution and income effects of tax law changes. For the empirical counterpart of their model they replaced the continuous time derivative from the Slutsky equation with a discrete time change from period t-1 to t:

(1) $\Delta lny_{it} = \beta\Delta ln(1-\tau_{it}) + \gamma\Delta lnN^v_{it} + \varepsilon_{it},$

where $\Delta lny_{it} = lny_{it} - lny_{it-1}$, $\Delta ln(1-\tau_{it}) = ln(1-\tau_{it}) - ln(1-\tau_{it-1})$, and $\Delta lnN^v_{it} =$

$lnN_{it}^v - lnN_{it-1}^v$.[2]

In log first difference form $\beta$ is the compensated ETI. As Gruber and Saez found that $\gamma$ was near zero, or that income effects were small, most of the subsequent literature has ignored income effects in their empirical applications and thus remain silent on distinguishing whether the ETI reflects compensated or uncompensated effects. I follow the recent work and ignore income effects for the ETI model, but return later to this issue when I present labor supply estimates. The actual empirical model estimated in the literature is more akin to

(2) $\quad \Delta lny_{it} = \beta \Delta ln(1 - \tau_{it}) + \delta f(y_{it-1}) + x_{it}\theta + \mu_t + \varepsilon_{it},$

where $f(y_{it-1})$ is some function of lagged income such as the log of income or a spline in income to control for mean reversion in income growth as well as trends in inequality, $x_{it}$ is a vector of demographics, and $\mu_t$ is a control for aggregate time effects such as a linear trend or time dummies. Because the standard OLS assumption that $E[\Delta ln(1 - \tau_{it})\varepsilon_{it}] = 0$ is likely to be violated it is necessary to instrument for the endogenous regressor. Gruber and Saez (2002) propose an exactly identified model based on the instrument $(\Delta ln(1 \hat{-} \tau_{it})) = ln(1 - \hat{\tau_{it}}) - ln(1 - \tau_{it-1})$, where $\hat{\tau_{it}}$ is the marginal tax rate that the individual would face in year t if income in year t differed from its $t-1$ value only by an inflation adjustment. This synthetic marginal tax rate is valid provided that it only reflects changes in tax law and not potentially endogenous behavioral responses to the tax law changes. I begin by estimating equation (2) using a similar synthetic instrument in order to replicate tax panel estimates of the ETI using matched panels in the CPS, and then consider a number of extensions as described in the ensuing subsections.

### 3.3 Heterogeneity and Nonrandom Selection

Because taxpayer panels offer a parsimonious set of demographic controls, the ability to examine heterogeneity in the response of income to tax changes has largely been limited

[2]The theoretical model of Gruber and Saez (2002) refers to virtual nonlabor income, but for the empirical counterpart they use after-tax income.

to differences across the base-year income distribution. The ETI literature has found that the elasticity increases as one moves up the income distribution, suggesting that it is high income taxpayers driving the results. A concern, however, is that these estimates may be affected by mean reversion. As an alternative, the consumption and labor supply literatures have frequently examined differences in spending and hours worked decisions across education groups under the assumption that years of schooling is a better proxy for permanent income than current income (Blundell and MaCurdy (1999); Attanasio and Weber (2010)). Thus by examining how the ETI varies by education attainment I can potentially better isolate the response of taxpayers with higher permanent incomes. In the models below I augment equation (2) with $(\Delta ln(1-\tau_{it}) \times educ)$, where $educ$ is a vector of dummy variables for different levels of education attainment. Although education decisions may be affected by tax policy, with my sample of heads of household described below most formal education is completed and not likely to be affected by contemporaneous tax policy.

More generally, I am interested in understanding the roles of selection on observables and selection on unobservables on the ETI, i.e. situations in which the conditional mean $E[\varepsilon_{it}|\Delta ln(1-\tau_{it}), f(y_{it-1}), x_{it}, \mu_t,] \neq 0$. The typical paper in the literature truncates the data below some threshold – \$20,000 in Auten and Carroll (1999), \$10,000 in Gruber and Saez (2002) – and assumes that the data below the threshold are missing (conditionally) at random. This assumption precludes changes in labor force composition in response to tax reforms, and also drops many low-income families whose incomes tend to be highly volatile and increasingly so over the past three decades (Hardy and Ziliak (2012)). For example, Meyer and Rosenbaum (2001) attributed upwards of sixty percent of the increase in labor force participation of single mothers in the 1990s to expansions in the EITC. Many of these women do not work full time, and yet are quite responsive to tax and transfer policy, and thus could affect estimates of the ETI. To my knowledge this assumption has not been tested formally in the literature (though some authors have tested the robustness of results to alternative thresholds).

I adopt the control function approach to examine the role of nonrandom selection (Barnow *et al.* (1980)). Specifically, consider the function $g(x_{it})$ that can be appended to equation (2). For selection on observables $g(x_{it})$ is some linear or possibly nonlinear function of the observable demographics $x_{it}$. In this case I include a broader set of demographic controls that are available in the CPS beyond the baseline control for martial status, such as education and race. For selection on unobservables, I adopt the Heckman (1979) approach and set $\hat{g}_{it} = \lambda(m_{it}\hat{\eta})$, where $\lambda_{it} = \frac{\phi(\cdot)}{\phi(\cdot)}$ is the inverse Mills ratio defined as the ratio of the pdf to the cdf of the normal distribution, $m_{it}$ is a vector of demographics, $\hat{\eta}$ are the first-stage probit coefficients of the regression that income exceeds a threshold (e.g. $10,000 in real terms across two years). In this case, the Heckman selection term is identified both via nonlinearity of the function and exclusion restrictions of variables included in $m_{it}$ but not $x_{it}$ as described below.

### 3.4 A Cohort-Based Approach to Estimating the ETI

Instead of approximating the continuous time Slutsky equation with its discrete time analogue, an alternative to equation (1) is to specify a functional form for the static income supply model from the utility maximization problem

(3) $\quad lny = \beta ln(1-\tau) + \gamma lnN^v + x_{it}\phi + \varepsilon$

where the income and tax variables are now in log levels. This specification is akin to the typical static labor supply equation estimated in scores of papers, but with income replacing hours of work and the net-of-tax share replacing the after-tax wage. Again ignoring income effects, estimation of the model is complicated by the possible correlation of the net-of-tax share and the model error term. However, with access to repeated cross-sectional data on individuals i in time period t that can be grouped into cohorts c in time period t, I can invoke assumptions similar to Blundell *et al.* (1998) in their application to married womens labor supply:

(A.1) $\quad E[\varepsilon_{it}|c,t] = \alpha_c + \mu_t$

$$(A.2) \qquad (E[ln(1-\tau_{it})|c,t] - E[ln(1-\tau_{it})|c] - E[ln(1-\tau_{it})]^2) \neq 0$$

Here assumption A.1 implies the exclusion restrictions for identification are that unobservable differences in average taxable income across cohorts can be summarized by a permanent cohort effect ($\alpha_c$) and an additive time effect ($\mu_t$). Assumption A.2 states that the net-of-tax share grows differentially across the cohorts and is equivalent to a rank condition for identification. It requires that variation in the net-of-tax share remains after controlling for time and cohort effects, and thus offers a set of exclusion restrictions for identification via the full interaction of cohort and time effects.

With these assumptions, I implement the grouping estimator of Blundell *et al.* (1998) in two steps. The first step is to estimate the reduced-form prediction equation for the log of the net-of-tax share by regressing it on the demographics, cohort effects, time effects, and their interactions as

$$(4) \qquad ln(1-\tau_{it}) = x_{it}\rho + \alpha_c + \mu_t + \alpha_c \otimes \mu_t + u_{it}$$

where $u_{it}$ is an error term assumed to be uncorrelated with the observed covariates and latent heterogeneity. The equation is estimated via least squares on the sample of individuals with income greater than some threshold, which in my case is income in excess of \$10,000. The fitted residual, $\hat{u_{it}^{1-\tau}}$, is saved for use in the second stage. Next I estimate the income supply equation appending the saved residuals to control for the endogeneity of the net-of-tax share as

$$(5) \qquad ln(y_{it}) = \beta ln(1-\tau_{it}) + x_{it}\delta + \alpha_c + \mu_t + \rho \hat{u_{it}^{1-\tau}} + \varepsilon_{it}.$$

While this approach requires the use of individual level repeated cross section data, the same results can be obtained working with cohort means.[3]

Estimating equation (5) will provide consistent estimates of the ETI under A.1 and A.2. However, as Blundell *et al.* (1998) were interested in identifying the after-tax wage

[3]An equivalent approach would be to apply weighted least squares to the transformed regression $(\overline{ln(y_{ct})}) = \beta(\overline{ln(1-\tau_{ct})}) + \alpha_c + \mu_t + \varepsilon_{ct}$, where log income and log net-of-tax share variables are the cohort-year specific means, and the weight in the regression is the number of observations in each cohort-year (Blundell *et al.* (1998)). This is a standard within estimator but applied to cohort-mean data rather than individual level data. I utilize the individual level data in the paper to maintain consistency across estimators, but results reported are the same.

elasticity of labor supply among married women, a focal concern was possible nonrandom sample selection into work. Continuing with the cohort specification, I adopt their revised assumptions A.1 and A.2 as

(A.1) $E[\varepsilon_{it}|c,t,z] = \alpha_c + \mu_t + \rho\lambda_{ct}$

(A.2) $(E[ln?(1-\tau_{it})|c,t,z] - E[ln(1-\tau_{it})|c,z] - E[ln(1-\tau_{it})|t,z] - \rho\lambda_{ct})^2 \neq 0$

where $\lambda_{ct}$ is the inverse mills ratio ($\lambda_{ct} = \frac{\phi(\cdot)}{(\phi(\cdot)}$) evaluated at $\phi^{-1}(P_{ct})$, $P_{ct}$ is the sample proportion of a given cohort with incomes above the income threshold z, and $\phi^{-1}$ is the inverse normal distribution. Identification of the ETI from (A.2) now requires that net-of-tax shares change differentially across groups, over time, and over changes in sample composition above the threshold z. Implementation of this estimator is straightforward. An additional first stage equation for having income over the $10,000 threshold is estimated via probit maximum likelihood using the full sample of individuals. The inverse Mills ratio, $\hat{\lambda}_{ict}$ , for individual i in cohort c in time t is constructed using the fitted values and appended to the equation (5) to control for possible selection above the threshold.

### 3.5 Data

The primary economic and demographic information used in this paper comes from the Annual Social and Economic Supplement of the Current Population Survey (CPS) for calendar years 1979-2008 (interview years 1980-2009). The CPS contains rich data on labor and non-labor income as well as detailed family demographics - including those relevant for tax purposes (for example: marital status, dependents, etc.). I employ the data first as a short panel by matching individuals across annual files, and then as a repeated cross-section. My sample consists of family heads ages twenty-five to sixty, where a family is defined as two or more persons related by birth, marriage, or adoption. The following contains detailed information on the income and tax data used within this analysis as well as the matching procedure.

### 3.5.1 Income and Tax Data

I use two variants of income for the dependent variable akin to those used in much of the ETI literature. The first, broad (gross) income is defined as total family income less social security income. Total family income includes most components of income reported on Form 1040 such as earnings of the head (and spouse if present) as well unemployment compensation, worker compensation, social security, public assistance, retirement benefits, survivor benefits, interest income, dividends, rents, child support, alimony, financial assistance, and other income. Gruber and Saez (2002) exclude social security income and capital gains owing to their differential tax treatment over the 1980s, and we do so as well. The second, and more narrow, income definition is taxable income defined as broad income less estimated exemptions and deductions which are obtained from NBERs TAXSIM program. A disadvantage of CPS data relative to tax panel data is that information on many deductions (e.g. home mortgage interest expense, moving expenses, charitable contributions, and medical expenses) used to arrive at Adjusted Gross Income (AGI) and taxable income are not collected. While many of these are typically omitted in the literature in order to achieve a consistent definition over the years, my measure of taxable income will be less precise than those calculable from tax panel data. I therefore expect my estimates for taxable income elasticities to be on the low end of the literature.[4] My broad income measures, however, should be quite comparable to those used in the past literature.

Prior to our matching across waves described below, I delete those observations with imputed income as Bollinger and Hirsch (2006) show that such imputed data may impart bias in regression coefficients. In addition, I adopt the consistent set of income top codes constructed by Larrimore *et al.* (2009) to mitigate the influence of changes in Census top

[4]TAXSIM estimates whether the tax unit itemizes based on estimated state tax liability (which is deductible for itemizers in the U.S.) and other deductions such as home mortgage interest payments, child care expenses, and charitable contributions. Because the CPS does not collect information on these other deductions, whether or not a family is estimated to itemize largely depends on state tax liability. Across the sample period, I estimate that about one-fourth of the families itemize, which is 6-10 percentage points lower than reported by the IRS in a typical year (See http://www.taxpolicycenter.org/taxfacts/displayafact.cfm?Docid=173 ).

code procedures starting in the mid 1990s. Burkhauser *et al.* (2012) find that using the consistent top code method results in CPS measures of income inequality tracking those from proprietary tax return data better than (unadjusted) public-use CPS data. Unless noted otherwise, all income data are deflated by the Personal Consumption Expenditure (PCE) deflator with 2008 base year. Following Gruber and Saez (2002), I drop observations with real broad income less than $10,000.

Tax rates are estimated for each family in each year using the NBER TAXSIM program in conjunction with basic information on labor income, taxable nonlabor income, and dependents. I consider two marginal tax rate definitions: one is the sum of the federal and state tax rate, and the second is the sum of the federal, state, and FICA payroll tax rate. The federal and state taxes include the respective EITC code for each tax year and state, thus allowing for the possibility of negative tax payments. The FICA tax rate is the sum of the Social Security and Medicare payroll tax rates. Because the Social Security Wage Base is limited, individuals with wage income exceeding the limit will face a Social Security marginal tax rate of zero for this portion of the tax. Before 1991 the Medicare payroll tax was applied to the same base as Social Security, but the 1990 budget act removed the payroll tax base ceiling for the Medicare portion and thus it applies to all wage earnings. I assume that the family bears only the employee share of the payroll tax rate.

### 3.5.2 Longitudinally Linking CPS Families

The CPS employs a rotating survey design so that a respondent is in sample for four months, out eight months, and in another four months. This makes it possible to match approximately one-half of the sample from one March interview to the next. Following the recommended Census procedure I perform an initial match of individuals on the basis of five variables: month in sample (months one-four for year one, months five-eight for year two); gender; line number (unique person identifier); household identifier; and household number. I then cross check the initial match on three additional criteria: race, state of residence, and age of the individual. If the race or state of residence of the person changed we delete that observation, and if the age of the person falls or increases by more than two years (owing to the staggered timing of the initial and final interviews), then I delete those observations on the assumption that they were bad matches. These additional criteria were very important prior to the 1986 survey year, but thereafter the five base criteria match most observations. Lastly, in accordance with the literature, I exclude individuals whose marital status changes from one year to the next as large changes in income unrelated to tax policy are expected for this group. There were major survey redesigns in the 1980s and 1990s so it is not possible to match across the 1985-1986 waves and the 1995-1996 waves. This yields a matched time series across twenty-nine years with gaps in calendar years 1984-1985 and 1994-1995.

Declining match rates occur after the mid 1990s reflecting in part a rise in imputation within the CPS after adoption of computer-assisted (CATI-CAPI) interviewing. A possible concern with declining match rates is with sample attrition affecting our income series. Under the assumption that the probability of attrition is unobserved and time invariant (i.e., a fixed effect), then differencing the variable will remove the latent effect (Ziliak and Kniesner (1998); Wooldridge (2002)). If there is a time-varying factor loading on the unobserved heterogeneity then differencing will not eliminate potential attrition bias. A conservative interpretation, then, is that data from matched CPS provides estimates of the elasticity of taxable income among the population of non-movers.[5] Over the full period, 1979-2008, I obtain 198,428 two-year longitudinally matched observations when broad income is the dependent variable, and 196,486 observations for taxable income.[6]

Because the change in net-of-tax rates is endogenous to the change in income, I instrument the actual change in tax rates with a predicted tax change,$(\Delta ln(\widehat{1-\tau_{it}})$. To obtain

[5]It should be noted that I am using one year differences rather than three-year differences used in some studies. The use of one year differences may result in elasticities reflecting more income shifting behavior, but given the structure of the CPS design it is not possible to examine three-year differences.

[6]These observations only include individuals with broad income exceeding \$10,000 in year one. Sample sizes fall as the income definition narrows due to missing data or income values for which I cannot take logs (i.e. zeros or negatives).

$\tau_{it}$, I inflate each individuals year one income by the increase in the PCE and run it through TAXSIM as year two income. Lastly when allowing for non-random selection, I require additional control variables (exclusion restrictions) to predict the probability of having income over \$10,000. The set of variables selected for this purpose are state-level variables that change over time including employment per capita, the poverty rate, minimum wage, gross state product, personal income per capita, and the welfare (TANF) and food stamp (SNAP) benefits for a family of three. These are obtained from the University of Kentuckys Center for Poverty Research Welfare Database.[7] Summary statistics for the matched CPS data are shown in Appendix Table A2.1.1.

### 3.5.3 Constructing Cohort Data

For the cohort analysis of equations (4) and (5), I return to the initial cross-sectional CPS data set, but in addition to dropping observations with imputed incomes and using the consistent top code series of Larrimore *et al.* (2009), I also drop individuals whose month in sample is greater than four to ensure there are no repeat observations. This results in a repeated cross-section of over 400,000 individuals who are then grouped into thirteen five-year birth cohorts and three education levels (less than high school, high school only, and more than high school) for a total of thirty-nine five-year birth by education cohorts. Because the consistency of the grouping estimator is based in part on the number of observations per cell being large, I follow Blundell *et al.* (1998) and drop cohort-education cells with fewer than fifty observations.

Figure 3.1 shows the life-cycle net of tax rates plotted for the thirteen different birth cohorts by education level. It is clear that cohorts in the lowest education level have the highest net of tax shares (i.e. face the lowest marginal tax rates), while cohorts in the highest education group face the lowest after-tax shares. This is consistent with progressive taxation assuming income is rising with education attainment. Evidence of variation within

[7] See http://www.ukcpr.org/EconomicData/UKCPR_National_Data_Set_12_14_11.xlsx

the education groups is also present, which is necessary for identification of the grouping estimator. For example, among birth cohorts with more than high school (3rd panel in Figure 1), at age forty the more recent cohorts face a higher net-of-tax share, which is consistent with tax reforms reducing marginal tax rates. Moreover, there appears to be a life-cycle trend of rising net of tax shares, which in this case appears more pronounced for the older cohorts. Summary statistics for the repeated cross-sectional CPS data are shown in Appendix Table A2.1.2.

## 3.6 Results

My first objective is to use matched two-year samples from the CPS along with the canonical ETI specification and identification strategy in equation (2) to attempt to replicate the baseline results from Gruber and Saez (2002). All instrumental variables regressions control for marital status and time dummies for initial year, and are weighted by year one broad income.[8]

Table 3.1 contains the baseline estimates where for ease of presentation I report only the elasticity of taxable income. The table has two rows corresponding to the control for mean reversion: one with a 10 piece spline in year-one log income, and the other with the level of year-one log income. For each of the income definitions (broad income and taxable income), I estimate the model with the two different marginal tax rates, one with and one without FICA.

The baseline broad-income estimate of 0.217 for the model with the net of tax share based on the federal and state tax rate is remarkably similar to, and indeed slightly higher than, the one-year difference estimate of 0.192 in Gruber and Saez (2002, Table 4). It is also quite close to the modal tax-panel estimate of 0.25 reported in Saez *et al.* (2012). The corresponding taxable income estimate of 0.272 is higher than the broad income ETI as expected, but lower than the 0.410 estimate in Gruber and Saez. The latter is not surprising

[8]Following Gruber and Saez (2002) I censor the level of broad income at $1 million in constructing weights.

because the taxpayer panel has more information on deductions than in the CPS. While we have greatest confidence in the broad-income estimates of the ETI from the CPS, collectively the baseline results suggest that matched panels from the CPS can produce estimates of the ETI in line with those from taxpayer panels.[9]

The second column under each income measure in Table 3.1 shows the corresponding estimate of the ETI with the inclusion of the FICA payroll tax. Here we see the estimate fall by about one half from the baseline. Mitrusi and Poterba (2000) document a substantial rise in the burden of payroll taxes, and a practical implication of that is seen in Appendix Table A2.1 where the average net of tax share is about 5.5 percentage points lower with FICA than without, and this gap rose from 3.7 percentage points in 1979 to 6.25 percentage points in 2007. In effect, the expansion of the payroll tax base over time (and rates were increased until 1991) partially negated the federal income tax changes associated with the tax reforms in recent decades. This resulted in reduced variation in the combined tax rate across workers over time, and in turn the potential variation used to identify the ETI.

Before proceeding with the discussion of selection and heterogeneity, I note that the ETI literature has conducted a number of specification checks on the canonical model. These tests often center on the role of weighting the regression model, the sample period, and whether and how one controls for regression to the mean effects. I conduct several of these tests and report them for completeness in Appendix Table A2.2.1. Similar to others I find that income weighting the regression model is important for identifying the ETI. While there is in general a lack of agreement on the merits of weighting regression models (Hoem (1989); Deaton (1997)), the argument to weight the ETI by income is model driven. Specifically, for optimal tax calculations the income response to changes in the marginal tax rate is proportional to the ETI times income and thus by income weighting we explicitly allow the ETI to vary with income (Gruber and Saez (2002)). Because of

[9] I note that the first stage regression of the actual change in log net of tax share on the change in the synthetic log net of tax share (controlling for the other factors) is very strong. The adjusted R-squared is 0.2, the Wald test of joint significance is in excess of 1000 (p-value $< 0.000$), and the size and significance of the synthetic tax rate is large.

the coherence with the underlying optimal tax model, I proceed with income weighting for the remainder of the analysis. I also examine my estimates restricting attention to the Gruber and Saez sample period, where the estimates of the ETI are a bit smaller owing to the fewer tax reforms to identify the effect. Last, in addition to using the 10-decile spline of log income, I examine a less parametric version of the spline by including dummy variables for each decile of the initial year income distribution. Similar to others in the literature I find identification of the ETI is sensitive to the specification of regression to the mean effects, whereby more flexible parameterizations can absorb the variation needed to estimate the ETI. I focus our remaining discussion on the 10-piece spline, and note in passing that a full set of results with the initial income deciles are available upon request.

### 3.6.1 Selection and Heterogeneity in the ETI

I extend the parsimonious benchmark model of equation (2) by examining the roles of selection and heterogeneity in the response of the ETI. I first append additional demographics to more completely control for selection on observables. This includes a quadratic in age, education attainment (dummies for high school, some college, college, and graduate degree, with less than high school the omitted group), indicators for children under the age of 6 and under 18, race (indicators for African American, Other , with white as the omitted group), and gender. I also include a complete set of state fixed effects to control for time-invariant factors across states that may affect income. I then examine heterogeneity in the ETI by interacting the change in log net of tax share with indicators for education attainment at the some college, college, and graduate levels.

Columns (1) and (3) of Table 3.2 show that the ETI falls by one-third for broad income and over forty percent for taxable income relative to the benchmark models in Table 1. In results not tabulated I re-estimated the models by only adding state fixed effects and not the other demographics and the ETI fell only by about five percent, suggesting that most of the reduction owes to selection on observable demographics. In columns (2) and (4) of

Table 3.2 I find a very strong positive gradient on the ETI based on education. Specifically, relative to a household head with a high school diploma, a head with a college degree has an ETI twice as high (0.588 versus 0.207 for broad income and no FICA tax), and a head with a graduate degree has yet again an ETI over twice as high as the college graduate. These estimates suggest that identification of the ETI is driven by the highly skilled, i.e. those with permanently higher incomes.

In Table 3.3 I go a step further to examine the role of selection on unobservables. The top panel simply appends the inverse Mills ratio to the base model reported in Table 3.1, while the second panel also includes the additional observed demographics and state fixed effects that control more comprehensively for selection on observables. In the first step, I estimate a probit model of the probability that income exceeds \$10,000 in both years, and construct the inverse Mills ratio using the index function from the estimated probit. I use both individual-level demographics and state-level socioeconomic variables described in the Data section as exclusion restrictions to assist in identifying the selection term in the top panel, and just state-level variables in the bottom panel (since those individual-level demographics are entered directly in the regression model in the lower panel). The estimates indicate that there is strong evidence of nonrandom selection on unobservables, again with the estimated ETI between thirty and forty percent lower than the base case depending on whether we examine broad income or taxable income. Perhaps surprising, though, Table 3.3 indicates that what matters for the ETI is whether one controls for selection, and not the form of selection. That is, comparing Tables 3.2-3.3 shows that I get similar estimates for the ETI whether I just include observed demographics (selection on observables) or model formally selection on unobservables.

In Table 3.4 I explore further which of the demographics have the most influence on ETI estimates. Column (1) presents the elasticity estimate for broad income when controlling only for marital status and time effects. In column (2) the set of controls is expanded to include gender, age, and controls for children which results in a reduction of the ETI estimate of roughly twelve percent. Parameter estimates fall another 25 percent once education and race are included in the set of controls as shown in column (3). Parallel estimates for the elasticity of taxable income are presented in columns 4-6 and display a similar pattern. Because estimates can vary depending on whether education and race are added in before age/gender/state effects instead of after as reported in Table 3. 4, in results not tabulated I reversed the order of operation and obtained similar results that race and education have the largest effects. Overall, the results indicate that race and education, which are generally not available in taxpayer panel data, are the demographic characteristics that exert the most influence on ETI estimates.

### 3.6.2 Repeated Cross-Section Cohort Models

Next I examine the robustness of the ETI to the alternative identification scheme of cohorts applied to the repeated cross-section samples of the CPS. This involves invoking assumptions (A.1) and (A.2) for the estimation of equation (5), and assumptions (A.1) and (A.2) with the addition of the inverse Mills ratio, $\hat{\lambda}_{ict}$ , to control for selection on unobservables.

Table 3.5 presents the results weighted by broad income, while Table 3.6 presents weighted estimates that also control for lagged cohort income. In the repeated cross section model I do not follow the same person over time, but I do follow cohorts. Thus, in a bid to control for changes in income inequality akin to the matched panel models, I include a control for the log of lagged cohort mean income (Verbeek and Vella (2005)). In column (1) of Tables 3.5 and 3.6 labeled "baseline" I present estimates of equation (5) with the most parsimonious set of controls (single, married). The second column contains estimates when the set of demographic control variables is augmented to include race, gender, indicators for children under age six and under age eighteen, and state fixed effects.[10] The third column appends the inverse Mills ratio.

The ETI estimates presented in columns (1) to (3) of Tables 3.5 and 3.6 are overwhelm-

[10] Age and educational indicators are omitted from the set of controls as they used to construct the cohort groupings.

ingly negative, both quantitatively and statistically, suggesting that the model is not robust to this alternative identification strategy. The inclusion of additional demographics and the inverse Mills ratio reduces the absolute value of the coefficients but estimates remain negative. Likewise, controlling for the lagged cohort mean income in Table 3.6 brings the estimates closer to zero (except when FICA is included), but they are still inconsistent with theory. These results are surprising, but column (4) in Tables 3.5 and 3.6 provides some clarity. Recall that the cohort model is identified via the first-stage exclusion restrictions of the interactions of cohort effects and time effects in equation (4). Again the requirement is that the change in log net of tax share grow differentially over cohort and time. In column (4) I drop controls for time effects in the second-stage equation (5), so I weaken the requirement that variation grow differentially over cohort. Positive ETI estimates are now obtained when time effects are omitted from the model. This suggests that there is not adequate variation across birth-year by education cohorts over time in net-of-tax shares over and above the generic time effect.

To explore identification of the cohort model further, I turn to the familiar labor supply model where the dependent variable is annual hours of work and the focal regressors are the after-tax wage rate and virtual nonlabor income. I do so because the grouping estimator for the ETI in equation (5) requires variation in the net-of-tax share over and above the fixed cohort and time effects, whereas the labor supply model makes use of variation arising from the same tax reforms, but also gets implicit variation in the pre-tax wage structure owing to technological change and other factors across cohorts and time. To my knowledge the Blundell *et al.* (1998) labor supply model has not been applied to samples of men and women in the U.S. (their data was married women in the U.K.), and thus it is instructive to examine whether the surprising negative ETI estimates we obtained from the cohort model carry over to the labor supply case.

Specifically, estimation of the hours worked model requires two steps. The first step is to estimate the reduced-form prediction equations for net wages (inclusive of FICA), virtual income, labor force participation, and having an income greater than \$10,000.[11] Let the vector of first stage dependent variables be denoted by $d_{it}^{r} = [lnw_{it}, N_{it}^{v}, P_{it}, I_{it}]$, and the vector of covariates as $Z_{it}^{r}$. Then the reduced-form equations are

(6) $$d_{it}^{r} = Z_{it}^{r}\rho + \alpha_c^r + \mu_t^r + \alpha_c^r \otimes \mu_t^r + \vartheta_{it}^r,$$

where r denotes the equation being estimated (i.e. net wage, virtual income, participation, income greater than \$10,000), $\alpha_c^r$ is a cohort effect, $\mu_t^r$ is a time effect, $\alpha_c^r \otimes \mu_t^r$ are interactions of cohort and time effects, and $\vartheta_{it}^r$ is an error term assumed to be uncorrelated with the observed covariates and latent heterogeneity (I also include state fixed effects in the first and second stages).

Following Blundell *et al.* (1998), I estimate the equations for the after-tax wage and virtual income via least squares on the sample of workers only, saving the fitted residuals $\hat{\vartheta}_{it}^{w}$ and $\hat{\vartheta}_{it}^{N^v}$. These residuals will be included in the hours worked equation to control for the endogeneity of the after tax wage and virtual income. The reduced form equations for employment and income greater than \$10,000 are estimated via probit maximum likelihood on the sample of workers and non-workers for all income levels, and those with income greater than \$10,000, respectively.[12] The parameters of these equations are used to construct sample selection correction terms. I then estimate the conditional hours worked equation via OLS for workers only with broad incomes of \$10,000 or more, appending the various controls for selection and endogeneity,

(7) $$h_{it} = \alpha + \beta lnw_{it} + \gamma N_{it}^{v} + X_{it} + \alpha_c + \mu_t + \theta_w \hat{\vartheta}_{it}^{w} + \theta_N \hat{\vartheta}_{it}^{N^v} + \delta \hat{\lambda}_{it} + \varepsilon_{it}.$$

Table 3.7 contains the results for the hours worked equation separately for men and women, where I include selection corrections for the decision to work and for broad income in excess of \$10,000. There are three specifications for each of men and women that vary

[11] A prediction equation for income greater than \$10,000 is not typical in the labor supply literature. It is included here to keep the labor supply analysis as parallel as possible to the ETI analysis.

[12] Variables needed for the estimation of the labor supply models are constructed as follows. Wages are constructed as the ratio of annual earnings to annual hours of work (annual weeks worked times usual hours per week). The earnings variable includes income from self-employment. I retain self-employed individuals to keep the samples used across the ETI and labor supply analyses consistent. The after-tax wage is constructed using the marginal tax rates described above. Observations with wages exceeding \$500 per hour are dropped from the sample.

based on how virtual nonlabor income is defined. In column (1) virtual income is family income less own workers earnings and family tax payments, plus an adjustment based on the mtr times own worker earnings; column (2) defines virtual income as family income less own workers earnings and family tax payments, plus an adjustment based on the mtr times family earnings; column (3) defines virtual income as family income less family earnings and family tax payments, plus an adjustment based on the mtr times family earnings. The latter specification flows out of a joint model of labor supply where spouses earnings are not included in nonlabor income. Each specification controls for marital status, the number of kids under age 6, the number of kids under age 18, race, and cohort, year, and state fixed effects.

All models produce positive uncompensated and compensated wage effects, while virtual non-labor income effects are negative and significant for men and statistically zero for women. There is substantial evidence that it is important to control both for the endogeneity of wages and virtual income, as well as nonrandom selection into work and for broad incomes in excess of $10,000. The bottom panel contains the corresponding wage and income elasticities evaluated at the mean of hours. For males I obtain uncompensated wage elasticities between 0.04-0.06 and compensated wage elasticities between 0.08-0.35. For women, uncompensated wage elasticities are about 0.12, and given the near zero income effects, the compensated elasticities are similar in magnitude. Both sets of estimates are well within the range found in the survey on labor supply and taxation by Keane (2011). These significant work disincentive effects of taxation in Table 7 suggest that the additional variation in the pre-tax wage structure provides much needed power to identify the model that is not available in the standard ETI model relying on tax reforms alone.

### 3.6.3 Combining Matched Panel with Cohort Identification

An attraction of the canonical first-difference ETI model in equation (2) based on matched panels over the cohort model in equation (5) is that the first difference model nets out person-specific and time-invariant heterogeneity in the log levels of income, whereas the cohort model assumes that unobserved preferences are homogeneous within cohorts and only vary across cohorts. If the latter assumption is violated then the cohort estimates are not consistent and the Gruber-Saez framework of equation (2) is preferred. At the same token, the synthetic tax rate instrument proposed by Gruber and Saez (2002) and used in most of the ETI literature has not gone without criticism (Moffitt and Wilhelm (2000); Blomquist and Selin (2010); Weber (2011)). It is well recognized that this instrument, which is a function of income in year t-1, $(y_{it-1})$, may be correlated with the error term. Researchers have attempted to remedy this problem by including different controls for $f(y_{it-1})$. However, Weber (2011) presents evidence that the instrument remains endogenous regardless of the additional income controls. She instead suggests using further lags of $ln(y_{it-1})$ to construct the predicted tax rate instrument akin to some panel-based labor supply models (Ziliak and Kniesner (1999), (2005)).

With only two years of individual level data in the matched CPS I cannot use further lags as instruments; however, I utilize an alternative approach by replacing the synthetic tax rate instrument, $ln\{(1-\hat{\tau_{it}})/(1-\tau_{it-1})\}$, with an instrument based on my cohort grouping strategy. Specifically, I first instrumented the change in an individuals net-of-tax share with the cohort-year mean change in the log net-of-tax share, $\overline{ln\{(1-\hat{\tau_{it}})/(1-\tau_{it-1})\}}_{ct}$. This resulted in highly variable and nonsensical estimates ranging from 0.4 to 4 and with standard errors ranging from one to two, or thirty times larger than those in the baseline models of Table 3.1. This likely stems from inadequate variation in the net of tax share across cohorts and years akin to that described in the last section. Instead, I take advantage of the fact that I identify the state of residence and that tax rates vary across states and time and thus construct an instrument based on state-cohort-year mean change in the log net-of-tax share, $\overline{ln\{(1-\tau_{it})/(1-\tau_{it-1})\}}_{sct}$. This instrument is plausibly more exogenous because the correlation between the group mean tax rate and the idiosyncratic error term is likely to be negligible. Results are shown in Table 3.8. My preferred estimates, which include FICA in the tax rate and control for selection on observables and unobservables, yield an ETI in the range of 0.4-0.5. This suggests that using state-cohort-year variation in conjunction with panel data offers a potentially fruitful identification strategy for ETI models, even in taxpayer panels.[13] I note that because tax panels may not contain measures of education, it is not possible to implement the estimator in the same way. Thus, as an additional check I re-estimated the model where instead of interacting year-of-birth with education to define a cohort I just used the thirteen year-of-birth cohorts interacted with state and year. The ETI using the synthetic net-of-tax share instrument at the state-birth cohort-year level was quite similar, in the range of 0.35-0.5.

## 3.7 Conclusion

I present new estimates of the elasticity of taxable income using matched panels and repeated cross sectional data from the Current Population Survey. With few exceptions the literature has relied upon taxpayer panel data, and this is the first use of matched panels of the CPS to the ETI literature. Using the canonical specification and identification strategy I find estimates of the ETI of 0.22-0.27, which surround the midpoint estimate from taxpayer panels reported in the survey by Saez *et al.* (2012). This suggests that publically available data like the CPS in conjunction with tax data from TAXSIM are fruitful alternatives for tax-related research. This is underscored by the access to education attainment in the CPS that permitted us to document a strong positive education gradient in the ETI, implying that estimates of the ETI are driven by the highly skilled who have tend to possess high permanent incomes.

The estimates also showed the importance of controlling for the payroll tax and for se-

[13] I note that about twenty percent of the sample is in state-cohort-year cells with fewer than ten observations per cell, and eighty percent of the sample has fifty or fewer observations per cell. It is the prevalence of these more sparse cells that steered us away from implementing the grouping estimator in equation (5) by state-cohort-year instead of cohort-year. However, in results not tabulated we re-estimated the grouping model on state-cohort-year and found negative estimates of the ETI akin to those in Table 3.5. These sparse cells are less problematic for the state-cohort-year synthetic instrument in Table 3.8 provided that any measurement error in the instrument is uncorrelated with the model error (Wooldridge (2002)).

lection. When I include the payroll tax in the net-of-tax share I find that the ETI falls by about one-half. Given that the Social Security portion of FICA captures at least 80 percent of the family income distribution today, and the uncapped portion of the Medicare tax even more, the results suggest that the expanding scope of the payroll tax makes the tax structure more proportional, which has the effect of attenuating variation over workers and time in the net of tax share and thus the implicit variation used to identify the ETI. Likewise, non-random selection attenuates the ETI by about thirty percent. However, the results show that it does not matter whether one simply controls for selection on observables via inclusion of a wider set of demographics, or whether one controls formally for selection on unobservables. Because taxpayer panels often contain some demographics beyond marital status such as age, gender, number of dependents, and filing status, the estimates suggest that controlling flexibly for these confounding factors is important. However, tax panels generally do not contain information on race and education, and I found these to be the most important demographics affecting the ETI. Potentially more troubling is my finding that the identification of the ETI is fragile. Specifically, several authors have raised concerns that the synthetic net of tax share may be correlated with the model error term, and if true, this renders the typical estimates inconsistent. Because this is a just identifying assumption it is not testable. I find that if I use an alternative identification strategy based on a grouping estimator adopted from the labor supply literature, the estimated ETI is negative, contrary to theory. The same grouping estimator yields theory-consistent compensated wage elasticities of labor supply for men and women in the range of 0.08-0.35. The difference between the two stems from the fact that the wage elasticity of labor supply model is identified not only from differential effects of tax policy across cohorts, but also from differential changes in the pre-tax wage structure owing to other factors such as technological change. At first blush this suggests that the labor supply framework might provide a more robust approach to welfare analysis. In a bid to improve the robustness of ETI identification I combined insights from both the ETI and grouping approaches to construct a synthetic instrument that varies by state, cohort, and year. This more aggregate instrument is plausibly more exogenous and yields an ETI in the range of 0.4-0.5. Because it is possible to construct a similar state-cohort-year instrument in large taxpayer panels, my results suggest that this could be a fruitful alternative for identification for future research on the elasticity of taxable income.

**Figure 3.1 Life-Cycle Net of Tax Rate by Education**

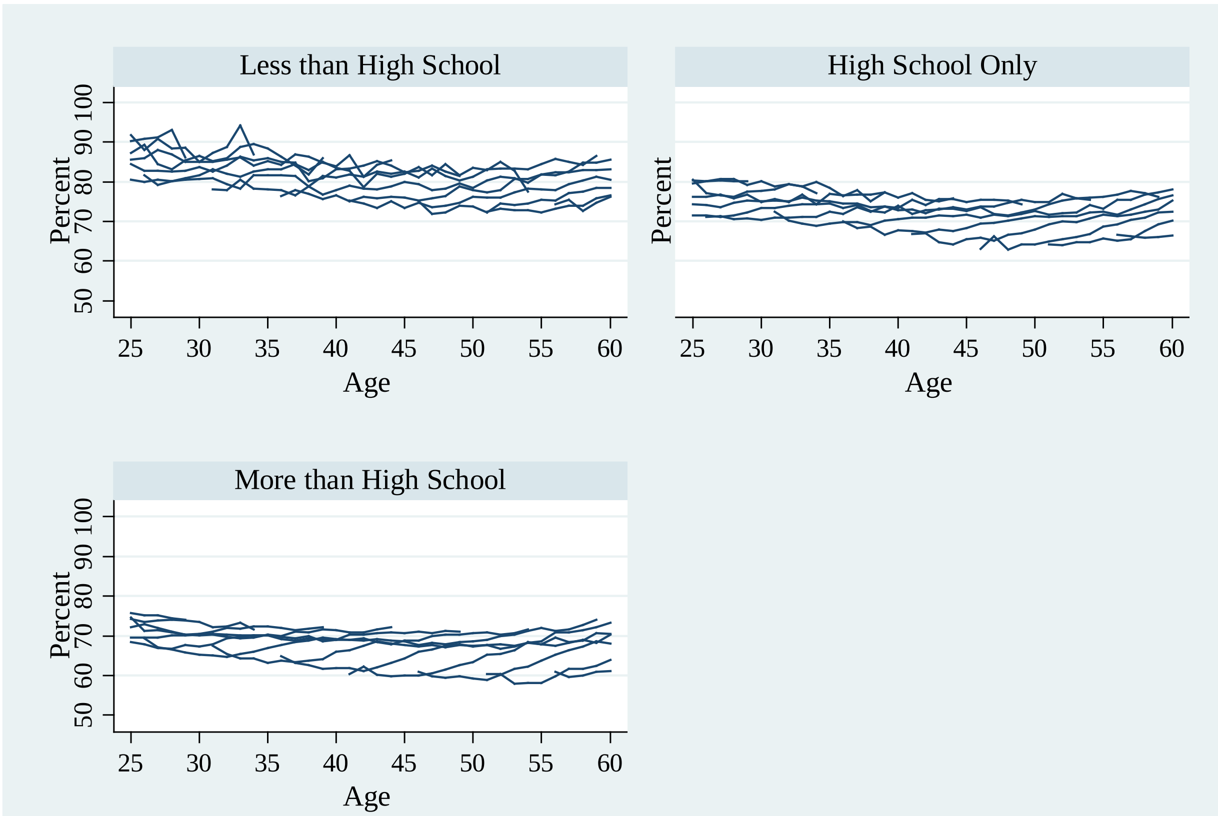


**Table 3.1 Baseline Estimates of the Elasticity of Taxable Income with Synthetic Tax Rate Instrument**

| | Broad Income | | Taxable Income | |
|---|---|---|---|---|
| | Fed + State | Fed +State+ Fica | Fed + State | Fed +State+ Fica |
| Spline of ln(income) | | | | |
| Elasticity | 0.217*** | 0.113*** | 0.272*** | 0.139*** |
| | (0.037) | (0.028) | (0.045) | (0.035) |
| ln(income) | | | | |
| Elasticity | 0.202*** | 0.098*** | 0.224*** | 0.108*** |
| | (0.034) | (0.027) | (0.040) | (0.032) |
| Observations | 198428 | 198427 | 196486 | 196485 |

Robust standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions are weighted by income and include controls for marital status and time effects for initial year. Income range is broad income greater than $10,000.

**Table 3.2 Demographics and Heterogeneity in the Elasticity of Taxable Income**

| | Broad Income | | | | Taxable Income | | | |
|---|---|---|---|---|---|---|---|---|
| | Fed + State | | Fed + State + Fica | | Fed + State | | Fed + State + Fica | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Elasticity | 0.144*** | -0.202*** | 0.075*** | -0.136*** | 0.159*** | -0.276*** | 0.084** | -0.179*** |
| | (0.035) | (0.045) | (0.027) | (0.035) | (0.043) | (0.057) | (0.034) | (0.046) |
| Elasticity* Some College | | 0.207*** | | 0.145** | | 0.302*** | | 0.199*** |
| | | -0.075 | | (0.060) | | -0.091 | | (0.073) |
| Elasticity*College | | 0.588*** | | 0.368*** | | 0.752*** | | 0.469*** |
| | | -0.099 | | (0.079) | | -0.114 | | (0.092) |
| Elasticity*Graduate Degree | | 1.181*** | | 0.717*** | | 1.368*** | | 0.831*** |
| | | -0.111 | | (0.089) | | -0.127 | | (0.102) |
| Observations | 198428 | 198428 | 198428 | 198428 | 196486 | 196486 | 196486 | 196486 |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted, include a 10 piece income spline, marital status, and time effects for initial year. The additional demographic controls are age, age squared, gender (female), race (controls for African American and other, with white as the omitted group), education (high school, some college, college, and graduate degree with less than high school as the omitted group), indicators for children under age 6 and 18, and state fixed effects. Income range is broad income over $10,000.

**Table 3.3 Estimates of the Elasticity of Taxable Income with Control for Non-random Sample Selection**

| | Broad Income | | Taxable Income | |
|---|---|---|---|---|
| | Fed+State | Fed+State+Fica | Fed+State | Fed+State+Fica |
| **With Selection** | | | | |
| Elasticity | 0.160*** | 0.066** | 0.216*** | 0.094*** |
| | (0.036) | (0.028) | (0.044) | (0.034) |
| Inverse Mills Ratio | -1.246*** | -1.227*** | -1.303*** | -1.281*** |
| | (0.033) | (0.032) | (0.051) | (0.049) |
| **With Selection & Controlling for Additional Demographics** | | | | |
| Elasticity | 0.145*** | 0.076*** | 0.160*** | 0.085** |
| | (0.035) | (0.027) | (0.043) | (0.034) |
| Inverse Mills Ratio | 0.079 | 0.076 | 0.054 | 0.049 |
| | (0.051) | (0.051) | (0.085) | (0.084) |
| Observations | 198428 | 198427 | 196486 | 196485 |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted, include a 10 piece income spline and controls for marital status and time effects for initial year. Additional demographics include age, age squared, gender (female), race (controls for African American and other, with white as the omitted group), education (high school, some college, college, and graduate degree with less than high school as the omitted group), indicators for children under age 6 and 18, and state fixed effects. Income range is broad income greater than $10,000.

**Table 3. 4 The impact of demographics on ETI estimates**

| | Broad Income | | | Taxable income | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Elasticity | 0.217*** | 0.191*** | 0.144*** | 0.272*** | 0.224*** | 0.159*** |
| | (0.037) | (0.036) | (0.035) | (0.045) | (0.045) | (0.043) |
| Controls include: | | | | | | |
| marital status | yes | yes | yes | yes | yes | yes |
| state effects | no | yes | yes | no | yes | yes |
| gender, age and children | no | yes | yes | no | yes | yes |
| race, education | no | no | yes | no | no | yes |
| Observations | 198428 | 198428 | 198428 | 196486 | 196486 | 196486 |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. The net of tax share is federal+state. All regressions are weighted, include a 10 piece income spline, marital status, and time effects for initial year. The additional demographic controls are age, age squared, gender (female), race (controls for African American and other, with white as the omitted group), education (high school, some college, college, and graduate degree with less than high school as the omitted group), indicators for children under age 6 and 18, and state fixed effects. Income range is broad income over $10,000.

**Table 3.5 Cohort-Based Estimates of the Elasticity of Taxable Income**

| | Broad Income | | | | Taxable Income | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| VARIABLES | Baseline | Additional demographics | Additional demographics and selection | no time | Baseline | Additional demographics | Additional demographics and selection | no time |
| Fed + State: | | | | | | | | |
| Elasticity | -2.631*** | -2.721*** | -2.686*** | 1.052*** | -2.593*** | -3.075*** | -3.005*** | 1.019*** |
| | (0.055) | (0.053) | (0.054) | (0.042) | (0.061) | (0.056) | (0.058) | (0.044) |
| Inverse Mills Ratio | | | -0.091*** | | | | -0.180*** | |
| | | | (0.027) | | | | (0.031) | |
| Fed + State + FICA: | | | | | | | | |
| Elasticity | -2.490*** | -0.560*** | -0.516*** | 1.085*** | -2.462*** | -0.616*** | -0.580*** | 1.010*** |
| | (0.073) | (0.116) | (0.114) | (0.044) | (0.080) | (0.128) | (0.127) | (0.046) |
| Inverse Mills Ratio | | | 0.171*** | | | | 0.140*** | |
| | | | (0.038) | | | | (0.042) | |
| Observations | 462864 | 462864 | 462864 | 462864 | 458441 | 458441 | 458441 | 458441 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted by broad income and include controls for marital status. Income range is broad income greater than $10,000. Additional demographics include gender (female), race (controls for African American and other, with white as the omitted group), indicators for children under age 6 and 18, and state fixed effects.

**Table 3.6 Cohort-Based Estimates of the Elasticity of Taxable Income with Control for Lagged Cohort Mean Income**

| | Broad Income | | | | Taxable Income | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| VARIABLES | Baseline | Additional demographics | Additional demographics and selection | no time | Baseline | Additional demographics | Additional demographics and selection | no time |
| Fed + State: | | | | | | | | |
| Elasticity | -1.408*** | -1.447*** | -1.469*** | 0.245*** | -2.646*** | -3.134*** | -3.070*** | 0.933*** |
| | (0.072) | (0.071) | (0.071) | (0.039) | (0.063) | (0.058) | (0.060) | (0.044) |
| Inverse Mills Ratio | | | 0.151*** | | | | -0.153*** | |
| | | | (0.034) | | | | (0.031) | |
| Fed + State + FICA: | | | | | | | | |
| Elasticity | -1.283*** | -1.351*** | -1.387*** | 0.157*** | -1.423*** | -1.774*** | -1.812*** | 0.107** |
| | (0.085) | (0.083) | (0.084) | (0.041) | (0.092) | (0.088) | (0.089) | (0.043) |
| Inverse Mills Ratio | | | 0.258*** | | | | 0.214*** | |
| | | | (0.037) | | | | (0.040) | |
| Observations | 462864 | 462864 | 462864 | 462864 | 458441 | 458441 | 458441 | 458441 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted by broad income and include controls for marital status and lagged cohort income. Income range is broad income greater than $10,000. Additional demographics include gender (female), race (controls for African American and other, with white as the omitted group), indicators for children under age 6 and 18, and state fixed effects.

**Table 3.7 A Cohort-Based Model of the Effects of Taxes on the Labor Supply of Men and Women**

| | Male | | | Female | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (1) | (2) | (3) |
| After-Tax Wage | 54.871** | 40.074* | 86.821*** | 89.559*** | 84.838*** | 94.178*** |
| | (21.823) | (21.727) | (22.084) | (28.151) | (28.216) | (27.759) |
| Virtual Non-Labor Income | -7.157*** | -3.283*** | -18.693*** | 0.606 | 0.847 | -3.475 |
| | (0.817) | (0.592) | (1.508) | (0.906) | (0.597) | (2.140) |
| Wage Residual | -145.144*** | -130.886*** | -177.959*** | -120.413*** | -116.274*** | -123.479*** |
| | (21.890) | (21.797) | (22.151) | (28.177) | (28.242) | (27.811) |
| Virtual Income Residual | 6.496*** | 2.999*** | 18.663*** | -2.970*** | -2.145*** | -0.020 |
| | (0.818) | (0.594) | (1.509) | (0.907) | (0.598) | (2.142) |
| Lambda (work) | -586.663*** | -574.550*** | -514.632*** | -91.285*** | -80.945** | -42.810 |
| | (31.354) | (32.018) | (30.338) | (32.559) | (32.708) | (31.903) |
| lambda2 (income > $10k) | 409.779*** | 410.753*** | 371.269*** | -83.594*** | -95.275*** | -163.605*** |
| | (31.584) | (31.655) | (31.551) | (29.717) | (29.785) | (29.668) |
| Uncompensated Wage Elasticity | 0.04 | 0.03 | 0.06 | 0.12 | 0.11 | 0.12 |
| Compensated Wage Elasticity | 0.15 | 0.08 | 0.35 | 0.11 | 0.10 | 0.16 |
| Income Elasticity | -0.11 | -0.05 | -0.29 | 0.01 | 0.01 | -0.04 |
| Observations | 295310 | 289010 | 289010 | 141136 | 132747 | 132747 |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. The mtr and tax payments include FICA. Each specification controls for marital status, children under age 6 and 18, race, and cohort, year, and state fixed effects. Column (1) defines virtual income as family income less own workers earnings plus an adjustment based on the mtr times worker earnings; column (2) defines virtual income as family income less own workers earnings plus an adjustment based on the mtr times family earnings; column (3) defines virtual income as family income less family earnings plus an adjustment based on the mtr times family earnings.

**Table 3.8 Estimates of the Elasticity of Taxable Income Using a Cohort-Mean Synthetic Instrument**

| | Broad Income | | Taxable Income | |
|---|---|---|---|---|
| | Fed + State | Fed + State + Fica | Fed + State | Fed + State + Fica |
| **Baseline** | | | | |
| Elasticity | 0.680*** | 0.569*** | 0.884*** | 0.724*** |
| | (0.238) | (0.128) | (0.303) | (0.170) |
| **With Selection & Controlling for Additional Demographics** | | | | |
| Elasticity | 0.456** | 0.408*** | 0.569** | 0.515*** |
| | (0.193) | (0.111) | (0.244) | (0.147) |
| Observations | 197939 | 197938 | 196020 | 196019 |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted, include a 10 piece income spline and controls for marital status and initial year. Income range is broad income greater than $10,000. Standard errors are clustered by cohort. Additional demographics include gender (female), race (controls for African and other, with white as the omitted group), indicators for children under age 6 and 18, and state fixed effects.

# 4 Estate Tax Competition and Migration: Examining Responses to the Repeal of the State Death Tax Credit

## 4.1 Introduction

On the eve of the fiscal cliff negotiations, the federal estate tax was among the many tax provisions being debated that was set to automatically revert to the 2001 policy rule in the absence of an agreement. The stakes for those with sizable estates were quite large given that failure to reach a compromise would result in the generous five million dollar exemption dropping to only one million dollars and the currently reduced top marginal tax rate of thirty-five percent climbing to fifty-five percent. On the other hand, estimates suggested that maintaining the current policy would cost the federal government over $335 million in revenue for the 2013 fiscal year and nearly $370 billion dollars over the next ten years.[14] Interestingly, the state governments also had much wrapped up in the fate of the federal estate tax - approximately three billion dollars for the 2013 fiscal year alone (Francis (2012)).

Historically, estate taxes have been imposed at both the federal and state level. And through most of recent history, they have been linked together through a federal credit initially implemented in 1924 to help counter the pressures of interstate competition.[15] The credit, known as the state death tax credit, directly offset one's federal estate tax burden by the amount paid to states up to a set maximum. The portion of the tax equal to the maximum federal credit became known as the pick-up or soak-up tax because it allowed the states to capture a share of the federal revenue without imposing any additional tax liability.

Over time the majority of states repealed their stand alone estate taxes in favor of reliance on the pick-up tax as their sole source of revenue from the taxation of estates. Con-

[14]The estimates were produce by the Joint Committee on Taxation in a document entitled "Estimated Revenue Effects of the Revenue Provisions Contained in an Amendment in the Nature of A Substitute to h.R.8, the "American Taxpayer Relief Act of 2012" as passed by the Senate on January 1, 2012"

[15]See section 4.3.1 for further discussion.

way and Rork (2004) investigated this phenomenon over the period 1976-1999 and found strong evidence suggesting interstate competition was the force behind this trend. By 2000, only twelve states imposed any tax liability in excess of the pick-up tax. Then, on the heels of nearly a century of growing uniformity in estate tax policy, Congress passed the Economic Growth and Tax Relief Reconciliation Act (EGTRRA) of 2001 which contained legislation fundamentally altering the estate tax landscape. Specifically, EGTRRA gradually phased out the federal estate tax and in the process of doing so, repealed the state death tax credit.[16] Interestingly, many states responded to the loss of their pick-up tax revenue by breaking ties with the federal government and retaining their taxes in a process known as "decoupling". Within just four years of its passage, EGTRRA had left the nation divided - with approximately half of the states imposing some form of estate tax while the other half did not.

This new divide in state level estate tax policy has rekindled fears of tax-induced migration and breathed new life into an almost dormant form of interstate competition. One need not look far for evidence of concern over the newly differentiated state estate tax policies. Headlines reading "Don't Die in New Jersey," "Reasons to Relocate" or "Where Not to Die in 2013" are easily found and highlight two questions of great interest regarding state estate taxation.[17] First, will states wishing to retain their estate taxes feel pressure from those that no longer impose any form of estate taxation? History, as well as recent policy decisions would suggest yes.[18] And second, will the affluent elderly begin to flow out of states with relatively unfavorable policies? In this regard, the evidence produced by a growing empirical literature examining tax-induced migration by the elderly seems to weigh more heavily towards no – though subtle differences in the more recent state estate tax landscape may make the reward to such behavior greater than in the past.

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[16]The 2001 EGTRRA is part of the legislation commonly referred to as the "Bush tax cuts." These provisions were initially set to sunset in 2011 but have since been extended as part of the 2010 Tax Relief, Unemployment Insurance Reauthorization and Creation Act and the more recent American Taxpayer Relief Act of 2012.

[17]Skinner (2011), Pane (1995), Forbes (2013)

[18]For instance both Kansas and Oklahoma repealed their estate taxes in 2010, while Ohio is slated to follow.

To address these intertwined questions, I empirically investigate spatial patterns in state estate tax policy for the decade following the 2001 reform. However, rather than relying on the commonly applied tax reaction function model, I begin with a structural simultaneous equation framework in which the estate tax base and estate tax rate are simultaneously determined. Specifically, I model the estate tax base as a function of a state's own estate tax rate and the estate tax rates in neighboring jurisdictions while the estate tax rate is modeled as a function of the state's available base and the policies being implemented in neighboring jurisdictions.[19] The advantage of such an approach is that it provides the researcher the ability to directly consider how a state's tax base may influence the selected tax policy through its size, political influence, and most importantly, its mobility - the factor presumed to be the causal influence behind the alleged tax competition behavior among states.

Results indicate a state's estate tax base is negatively influenced by its own tax rate and positively influenced by the tax rates in neighboring jurisdictions.[20] A state's estate tax rate is also positively influenced by the rates set in neighboring jurisdiction - consistent strategic policy behavior. Finally, some evidence is found suggesting a growing estate tax base may lead to a decline in the state's effective tax rate. The finding that states react to the tax policies set in neighboring jurisdictions combined with the responsiveness of the estate tax base provide strong support of estate tax competition. However, a state's estimated reaction to a ten percent cut in the tax rate of their neighbors is fairly large (an own tax cut ranging somewhere between 4-7.8 percent, depending on the definition of neighbors), while the reaction of the tax base seems much smaller. Specifically, a ten percent increase in a state's own estate tax rate is estimated to lead to a reduction in their estate tax base of only .3-1.5 percent suggesting the tax base mobility does not fully explain the observed tax reactions.

[19]Similar applications of simultaneous equation models include Shroder (1995) who studied the simultaneous determination of state welfare populations and benefit levels and Brett and Pinkse (2000) which examined the simultaneous determination of the municipal tax bases and rates in British Columbia.

[20]For the purpose of this analysis, two definitions of a state's "neighbors" are considered. The first is simply geographic neighbors (or boarding states) while the second is based on migration flows. More detail is provided section 4.4.1.

The remainder of the paper proceeds as follows. Section two briefly reviews the literature on interjurisdictional competition and base mobility with a focus on estate taxes and the elderly while section three provides the reader with some historical context on the taxation of estates and a detailed description of the recent policy landscape. Section four presents the empirical framework and econometric methods. Section five describes the data and measurement issues, section six presents the results, and section seven concludes and provides a discussion of future research.

## 4.2 Existing Literature

Fiscal reaction functions, in which one state's policies are a function of those selected by their neighbors, have been used extensively in the literature investigating the strategic policy setting behavior of decentralized governments. For instance, corporate, sales, excise, and property taxes have all been the subject of both theoretical and empirical investigations of strategic tax competition (Brueckner and Saavedra (2001), Devereux *et al.* (2002), Rork (2003), among others). Similarly, strategic policy setting over welfare benefits, state per capita expenditures, and expenditures on categories such as education and pollution abatement have also been examined (Figlio et. al (1999), Saavedra (2000b), Case *et al.* (1993), Baicker (2005), Fredriksson and Millimet (2002) among others). These studies typically turn up significant empirical evidence supporting the hypothesis that state governments are engaged in strategic policy setting though it is often unclear as to which channel explains this behavior (competition, yardstick competition, mimicking, common intellectual trend, etc.). To address this matter, researchers develop compelling arguments which favor competition as the driving factor behind their results. For instance, Figlio *et al.* (1999) present evidence of response asymmetries in a state's reaction to changes in their neighbors' welfare benefits (i.e. states respond stronger when neighbors cut benefits than when they increase them) and argue such findings are more consistent with a story of competition than the alternative explanations. Similarly, in a study of strategic tax competition, Devereux *et al.* (2002) show evidence that strategic interactions are only found for open economies (i.e. those without capital controls in place). Conway and Rork (2004) extended the empirical literature to include estimates of strategic reactions among states in the setting of their estate tax policies over the period 1967-1999. Strong evidence indicating states set estate tax policies interdependently is detected. To demonstrate the results were likely explained by tax competition rather than some other factor or spurious correlation, the authors split their sample into three periods - the 1970s, 1980s, and 1990s - and reestimate the model to confirm their hypothesis that competition should decline over time as more and more states hit the "bottom" created by the state death tax credit and could no longer manipulate their tax rates.

An alternative strategy for identifying competition is to directly estimate the mobility of the base that jurisdictions are assumed to be competing over. For instance, a voluminous empirical literature has investigated "welfare migration" or whether or not the poor gravitate towards states with more generous social programs (Gramlich and Laren (1984), Blank (1988), Levine and Zimmerman (1995), Walker (1994), McKinnish (2005, 2007), and Gelbach (2004)). Another growing literature has examined the locational decisions of seniors and whether they are influenced by estate taxes and other fiscal policies such as income tax breaks for the elderly (Bakija and Slemrod (2004), Conway and Rork (2006, 2008, 2011), Brülhart and Parchet (2010)). Locational decisions of individuals based on state income taxes and millionaire taxes have also recently been examined (Coomes and Hoyt (2008), Young and Varner (2011). Finally, Buettner (2003), Brett and Pinske (2000), and Riedl and Rocha-Akis (2009) examine the mobility of bases in the context of capital taxation.

Interestingly, the empirical findings of the fiscal reaction function based literatures and the approaches that directly investigate the mobility of the base are often seemingly self-contradictory - especially when the base consists of mobile individuals. For instance, there is ample empirical evidence of welfare competition (Figlio et. al (1999), Saavedra (2000)) and yet the evidence of welfare migration is typically minimal.[21] As previously discussed, regarding estate taxes, Conway and Rork (2004) documented strong evidence supporting the presence of interstate competition. However, in subsequent work these authors find no statistical evidence that the elderly react to state estate tax policies in making their migration decisions - in fact, they instead present evidence that the causality may run the other way (Conway and Rork (2006)), a possibility that will be considered in my empirical framework. Specifically they find that higher levels of elderly in-migration and especially net in-migration contribute to a higher probability of a state repealing or reducing its estate tax. An important caveat acknowledged by the authors is that residence choices of the very rich elderly may be impacted by estate taxes while overall elderly migration in the population aged sixty-five and up is not. This conclusion is supported by Bakija and Slemrod (2004) who find that high state estate taxes have a statistically significant, though small, negative impact on the number of federal estate returns filed. Additional evidence supporting the mobility of the wealthy elderly comes from Young and Varner (20011) who use a difference in difference strategy to study the response of the affluent to a millionaires tax enacted in the state of New Jersey. Though their results do not indicate much responsiveness in the overall millionaire tax base, two subgroups - rich people of retirement age, and those who earn their income from investments - are found to be responsive. Finally, in a study of bequest tax reforms in Swiss cantons, Brülhart and Parchet (2010) find that changing tax rates have essentially no effect on the relevant estate tax base.[22] What they do find is that inheritance tax revenues are increasing in inheritance tax rates even over the long run leading them to conclude that the alleged pressures of tax competition did not manifest in reality.

A third strategy for identifying competition over a mobile base combines these two approaches into one by considering the simultaneous determination of a jurisdiction's fiscal

[21] See for example Southwick (1981), Gramlich and Laren (1984), Blank (1988), Levine and Zimmerman (1995), Walker (1994), McKinnish (2005), McKinnish (2007b), and Gelbach (2004).

[22] Though negative tax rate effects are obtained in eighteen out of twenty specifications, the results are only weakly statistically significant in two cases when the most narrow definition of the tax base is used.

policy and the affected base. For instance, such an approach has been applied several times in the literature investigating strategic behavior in the determination of state welfare benefits and the migration of the poor (Shroder (1995), Berry *et al.* (2003)). Similarly, Brett and Pinske (2000) applied this strategy in their study of the determinants of municipal tax rates in British Columbia. By first developing a model in which a jurisdiction's tax rate and base are simultaneously determined and following it with an estimation of the system's reduced-form tax equation, the authors are able to decompose the reduced-form tax effect (how a jurisdiction responds to its neighbors taxes) into two components. Their analysis reveals the observed reduced-form result is explained largely by the influence of a jurisdiction's own tax base on the rate rather than the impact of neighbors' tax rates on the base. These methods can be advantageous as they provide the researcher the ability to identify both spatial patterns in tax policies, and more importantly, the mechanisms that explain them. Applying these methods to estate taxes is particularly appropriate given the commonly invoked argument that the rich will flee high tax states and the emerging spatial patterns in the post-EGTRAA estate tax landscape. Before proceeding to the empirical framework the following section offers background on the use of estate taxation in U.S. and a detailed description of the recent policy changes.

## 4.3 Estate Taxes

Estate taxes have existed in the United States for over 200 years. During the eighteenth and nineteenth centuries, federal estate taxes were actually enacted and subsequently repealed three times. Though each round of taxation took a different form, all were spawned from above ordinary revenue needs due to military activity and all were repealed upon the conflict's end.[23] State estate taxes have a history all their own which began in 1826 when Pennsylvania became the first state to impose an inheritance tax. Like their federal counter-

[23] See Gale and Slemrod (2000), and Cooper (2004) for more detailed histories of the federal estate tax. Cooper 2004 also provides a detailed history of state estate taxes. Unless otherwise noted, much of the following information is drawn from this source.

parts, state estate taxes were also initially in a state of flux. Over the first 65 years of their history, only a modest number of states enacted such taxes and those that did frequently amended or repealed them after a short while.[24] At the turn of the century however, a new pattern emerged in state death taxation. Between 1892 and 1916 thirty-four states enacted estate taxes. And unlike the initial set of state estate taxes, the taxes created by newer legislation adopted more progressive rate structures and were of greater fiscal consequence. However, by 1916, the year the federal estate tax returned due to wartime pressures, state estate taxes had begun to slide into a period of relative decline. While the encroachment by the federal government into the estate tax arena played some role in this new trend, many felt the real reason laid elsewhere, specifically, tax havens such as Florida.

### 4.3.1 Interstate Competition and the Federal Solution

A few rogue states had strategically failed to adopt any form of estate taxation in the pursuit of tax haven status. As a result, the fear of estate tax-induced migration by wealthy populations had begun to sweep the nation. Florida, the original tax haven, was soon joined by Alabama, while Nevada and California were preparing to follow suit. State policy makers felt they would soon be faced with a choice - repeal your estate tax or lose some wealthy residents. Congress attempted to intervene in 1924 by enacting a state death tax credit but its cap at twenty-five percent of the federal tax made it too low to have a significant impact. Between 1924 and 1926 three national conferences were held to address the matter, but it soon became clear that the states could not solve the problem alone. Finally at the last convention a compromise was reached: Congress would continue to impose a federal estate tax with approval of the states but the state death tax credit would be expanded to grant the states eighty percent of this revenue. As long as Congress continued to impose a federal estate tax, states would have an incentive to impose their own estate taxes approximately

[24] For example Massachusetts imposed an estate tax in1841 which was repealed only two years later. Wisconsin's 1868 estate tax lasted only four years. Alabama's 1848 estate tax was amended at least five times before its repeal in 1867.

equal to the federal credit.

### 4.3.2 Interstate Competition Returns

Over time all states eventually adopted the pick-up tax discussed above. However, prior to 1960, only four states chose to collect only the pick up portion of this tax -Alabama, Arkansas, Florida, and Georgia (Conway and Rork (2004)). The creation of the state death tax credit had allowed states to retain their traditional estate taxes and thus the remaining state legislators chose to levy additional estate taxes over and above those covered by the state death tax credit leaving a modest level of variation in state estate tax rates. Then in 1976, New Mexico became the first state to eliminate their traditional estate tax in favor of sole reliance on the pick-up tax. This move was quickly followed by the bordering states Utah, Arizona, and Colorado along with Vermont, Virginia and North Dakota.[25] By the year 2000, thirty-eight states imposed only the pick up tax and several more were slated to adopt this policy in the near future. Uniform estate taxation across the states seemed to be just around the corner. And then came EGTRRA followed by a string of state moves to "decouple" from the federal government. The story is illustrated graphically by Figure 1 which documents the coefficient of variation for estate tax revenues as a percentage of total state revenues over the past forty years. One can see an increase in variability corresponding perfectly with the start of the pick-up tax revolution in 1976. This trend turns downward by the late eighties as more and more states became pick-up only states. Then, right around 2002 - the year in which states would first feel the impact of EGTRRA, the trend begins to climb.

### 4.3.3 Post EGTRRA Landscape

Following the passage of EGTRRA, the federal estate tax was gradually phased out through a scheduled series of increases in the exclusion amount and marginal tax rate reductions

[25]See Conway and Rork (2004) for a chronology of state actions to remove their estate inheritance and gift taxes over the period of 1976-2003.

until its full repeal in 2010.[26] The credit for state death taxes faced a much quicker phase out. Specifically, the credit was reduced by twenty-five percent each year beginning in 2002. Full elimination of the credit took effect in 2005 at which point a deduction became available to those living (or owning property) in states that continued to impose some form of estate taxation.[27] Figure 2 shows the gradual phase out of the federal estate tax with the schedule for the exclusion amounts and top marginal rates from 2001 through the current year. Figure 3 illustrates the changing state and federal revenue shares of a hypothetical estate worth three million dollars in a state imposing only the pick-up tax as the tax cuts were phased in. As one can see, the loss of pick-up tax revenue was quickly felt by states taking no action to retain their estate taxes. This point is further illustrated by Figure 4 which plots the federal net estate tax collected against the revenue transferred to the states through the state death tax credit and deduction that took effect in 2005. From the the figure one can see the revenue hit to the states was immediate while the federal revenue stayed somewhat level (in part due to the pick-up tax revenue no longer transferred to the states) until the exclusion amount increased into the higher two and three and one half million dollar range.[28] After the year 2005, the revenue transferred to the states due to the deduction rose for a period and then began declining around 2008. This is likely explained by the movement of many states to "decouple" from the federal government.

Decoupling refers to a process through which states can sever ties with the federal

[26] Under EGTRRA's sunset provision, these tax reductions were set to expire at the end of 2010 with the estate tax reverting back to its pre-EGTRRA schedule for 2011. However subsequent legislation extended the tax cuts by reinstating the estate tax with a five million dollar exclusion and top rate of thirty-five percent through 2012. In the absence of this change, the exclusion amount would have returned to one million dollars with a top rate of fifty-five percent.The legislation extending the cuts was known as the Tax Relief, Unemployment Insurance Reauthorization and Job Creation Act of 2010. Subsequent legislation created as part of the 2013 Fiscal Cliff negotiations has set a new four million dollar exclusion with a top rate of forty percent.

[27] On December 1, 2005, twenty-three states and the District of Columbia has some form of estate, gift, or inheritance tax in place (Cooper (2004))

[28] Graetz and Shapiro (2005) provide an interesting discussion of the political maneuvering that went into obtaining a full (though temporary) repeal of the federal estate tax. They highlight that initial legislation provided for "equal treatment of the states" meaning their revenue would be reduced at the same rate as the federal government. However, as the bill made its way through the Senate Finance Committee the state revenue phase out was accelerated to keep the total revenue cost of the tax bill down. State lawmakers took action to oppose this change but were unsuccessful.

government's estate tax code. Doing so allows a state to retain their estate tax revenues which would have otherwise been phased out and fully eliminated with the pick-up tax in 2005. Rather than creating new estate tax systems, most states decoupled through simply referencing the federal estate code (specifically the maximum credit for state death taxes) at a pre-EGTRRA date.[29] Three states including Connecticut, Nebraska, and Washington opted to enact their own stand alone estate taxes (McNichol et. al (2003), McNichol (2006), Conway and Rork (2004)). Figure 5 shows the percentage of states collecting only the pick-up tax over the last decade. In 2001, roughly seventy percent of states relied fully on the pick-up tax. By 2005, the percentage had dropped close to 50 percent and then began to creep back up as several states that had initially retained their taxes moved to repeal them.[30]

As discussed above, the majority of decoupled states simply continued to impose an estate tax equal to what the tax would have been under the old federal schedule for the maximum credit for state death taxes. This schedule had a progressive marginal tax rate structure with a minimum rate of eight-tenths of a percent (for adjusted taxable estates valued $40,000 or more) and a top rate of sixteen percent (for adjusted taxable estates valued at $10,040,000 or more).[31] However, most decoupled states chose their own exemption amounts which differed from the exemption amount schedule being followed by the federal government. For instance, Kansas, Maine, Maryland, Massachusetts, Minnesota, New York, Oregon, Tennessee, and the District of Columbia chose to keep their exemption equal to $1,000,000 while the federal exemption amount climbed to $1,500,000; $2,000,000; $3,500,000; and $5,000,000. Only North Carolina and Delaware allowed their state thresholds to climb all the way to the $5,000,000 federal exemption level. Ohio had the lowest

[29]The laws in some states -Kansas, New York, Ohio, Oregon, Virginia, Washington, and the District of Columbia - already reference pre-EGTRAA law and thus decoupling occurred automatically if lawmakers failed to update the reference. Other states –Illinois, Maine, Maryland, Massachusetts, Minnesota, Nebraska, New Jersey, North Carolina, Pennsylvania, Rhode Island, Vermont, and Wisconsin – had to take action to decouple which involved passing legislation linking their estate law to the pre-EGTRRA federal law.

[30] Appendix Figure 1 provides a timeline of legislative changes made to estate tax policy following the passage of EGTRRA.

[31]See appendix Figure A2 for schedule.

estate tax exemption followed by New Jersey with respective thresholds of \$338,330 and \$675,000. States imposing inheritance taxes had even lower thresholds. This resulted in a tax gap where estates of certain values could be subject to a state tax without being subject to the federal tax. This gap between the value of the estate subject to state taxation but not federal taxation is depicted in Figure 6 which plots both the mean and maximum tax gap. One can see the gap rose quickly over the past years as some state chose to retain low exemption levels.

The previous discussion highlights the fact that considerable variation continues to exist in the estate tax policies set by state governments. Furthermore, by tracing out the recent changes in state estate tax policy one can see that these policies appear to be continuing in a state of fluctuation. To gain a deeper understanding in the factors determining state estate tax policies, I now turn to my empirical investigation. The following section describes the empirical framework.

### 4.4 Empirical Framework

Much of the recent policy debate surrounding state level estate taxes is based upon two notions. At the individual level, tax differentials can hypothetically induce an exodus of wealthy taxpayers from high tax states to a growing number of low or no tax states. Similarly, at the state level, concern over this outcome can lead states to reduce or abandon their estate taxes. The hypotheses surrounding the situation can be described with the setup put forth here. Assume there is a country made up of 2 states, state i and state j. Let $m_i$ denote the proportion of millionaire retirees residing in state i and $t_i$ the estate tax they face. The estate tax rate in the other state is denoted by $t_j$ while $X_i$ and $Z_i$ denotes the vectors of other relevant state characteristics determining the locational decisions and tax rates. Then

$$m_i = f(t_i, t_j; X_i), \quad \frac{\partial m_i}{\partial t_i} < 0 \ \ and \ \ \frac{\partial m_i}{\partial t_{-i}} > 0 \tag{13}$$

$$t_i = f(t_j, m_i; Z_i), \;\; \frac{\partial t_i}{\partial t_{-i}} > 0 \;\; and \;\; \frac{\partial t_i}{\partial m_i} < \;\; or \;\; > 0 \tag{14}$$

Here we can see estate tax base, $m_i$ is a function of the estate tax base in a state's own jurisdiction as well as the alternative location and the estate tax rate is a function of the available base. All else equal we expect an increase in a state i's tax rate to have a negative influence on its tax base and increase the tax rate set in state j to have a positive influence on the base in state i. A positive relationship between a states own tax rate and the tax rate set in neighboring jurisdictions would also be expected under the tax tax competition scenario. Finally, we would also expect the available tax base to have an influence on the selected estate tax rate. However, this relationship is less clear. For instance, the fact that many states in New England (including New York, New Jersey, and Connecticut) chose to retain their estate taxes may well be explained by the fact that these states have relatively large potential estate tax bases which would make abandoning the tax more costly than in states like Wyoming or West Virginia. In this case we might expect a growing base to have a positive influence on the rate. Alternatively, if the citizens composing the tax base have political influence then we might expect the base to negatively influence the tax rate. As previously discussed, support for this hypothesis was presented in Conway and Rork (2006). Finally, it is possible that a growing tax base could also produce enough revenue to allow for a lower state tax rate or higher exclusion amount. Before introducing the empirical methodologies used to estimate this simultaneous equation model, I must first discuss the concept of neighborhood.

#### 4.4.1 Defining Neighbors

In the analysis, I seek to determined whether and to what extent a state's estate tax base depends on their own estate tax rate as well as the estate tax rates prevailing in competing states. In addition, I also investigate the extent to which a state's own estate tax rate is influenced by the estate tax rates in these competing states. The estimation of such models therefore requires one to specify in advance which states constitute competitors or "neighbors." Here I implement two intuitively appealing definitions of neighbors – one based simply on geography, the other on more complicated economic considerations. The first, WI, is a basic contiguity weighting scheme. Under this specification a state's competitors are simply their immediate geographic neighbors or the states with which they share a border. Specifically, states that do not share a common border with state i are signed are assigned zero weight, ($\omega_{ij} = 0$), while equal weights ($\omega_{ij} = 1/n_i$) are given to bordering states where $n_i$ is the number of states contiguous to i. While it is possible for individuals fleeing an unfavorable tax environment to consider only the closest states as alternative locations, this assumption is generally hard to palate given the historical population flows of the elderly and the fact that the mobile population under consideration is one of great financial means. And because states know that they do not only lose and receive elderly residents from their geographic neighbors, they too likely consider a wider set of states when setting their own estate tax rates. To address this matter I use data from the 2000 census to construct a second set of weights based on population flows of the elderly between 1995 and 2000. With this scheme state i assigns each state j a weight of $\omega_{ij} = e_{jt}/\sum_{j=1}^{n} e_{jt}$ where $e_{ij}$ is the number of elderly migrants to state i that lived in state j five years ago. I focus on migrations flows of the whole elderly population rather than a certain income class to avoid introducing additional endogeneity issues.

### 4.4.2 Econometric Methodology

The econometric model for the simultaneously determined estate tax base and estate tax rate is given below.

$$m_{it} = \phi t_{it} + \rho \sum_{i \neq j}^{48} \omega_{ij} t_{jt} + X_{it}\theta + \alpha_i + \delta_t + \mu_{it}$$

$$t_{it} = \eta m_{it} + \psi \sum_{i \neq j}^{48} \omega_{ij} t_{jt} + Z_{it}\beta + \zeta_i + \lambda_t + v_{it}, \tag{15}$$

Here the tax base for state i in time t is given by $m_{it}$ while $t_{it}$ is the states's own tax rate and $\sum_{i \neq j}^{48} \omega_{ij} t_{jt}$ is the tax rate in neighboring jurisdictions. The set of control variables included in the tax base equations are given $X_{it}$ while $\alpha_i$ and $\delta_t$ denote state and time fixed effects. Likewise, for the tax rate equation, $Z_{it}$ denotes the set of controls while $\zeta_i$ and $\lambda_t$ denote state and time fixed effects. Lastly, $\mu_{it}$ and $v_{it}$ represent the disturbance terms for the base and rate equations respectively. The coefficent, $\phi$, represents how a state's tax base responds to changes in their own state estate tax rate while, $\rho$ represents changes in a state's estate tax base due to changes in their neighbor's tax policy. In the tax rate equation, $\eta$, represents the influence of the tax base on the tax rate while, $\psi$, represents the response of a state's tax rate to the tax rates set in neighboring jurisdictions.

### 4.4.3 Estimation Issues

To obtain the most efficient estimates, the tax base and rate equations are estimated jointly using a generalized method of moments (GMM) estimation technique. More specifically I use the two-step GMM estimator with heteroskedacticity robust standard errors. In estimating the models given by equation (3), one must address the endogeneity of several of the regressors included in the model. To begin, the structure of the economic model implies that the tax rate is endogenously determined in the tax base equation while the tax base is endogenously determined in the tax rate equation. Furthermore, the inclusion of neighbor's tax policy introduces a second source of endogeneity to the model. Instruments are therefore required for the estimation of the system given by (3). A brief discussion of instrument choice is presented below followed by a more detailed account of all the model's variables contained in the data section.

The identification strategy adopted here is based on isolating a set of exclusion restrictions or factors expected to exogenously shift the tax rate (tax base) without directly influencing the tax base (tax rate) to serve as instruments in base equation (rate equation). Instruments for the estate tax rate in the base equation, or those factors excluded from the base equation include last year's state per capita debt, last years state per capita federal transfers, political variables including indicators for a republican majority and the political party of the governor, the percentage of the population age sixty-five and older and eighty-five and older, and several other factors believed to exogenously influence the tax rate. These instrument choices were influence in part by, Conway and Rork (2006) who included similar measures as exogenous controls for the estate tax rate in their model of estate tax competition.[32] An additional instrument selected for the estate tax rate is an indicator for states imposing only the pick up tax. While these variables could potentially have some influence on the tax base, the reasons are less apparent than their impact through the tax rate. Of these potential exclusion restrictions, the political variables, age variables, and the pick-up tax indicator are commonly statistically significant across specifications and thus identify the model. Instruments for the estate tax base include state spending on health and hospitals, welfare, education, and highways along with a set of variables that proxy for amenities (the percentage of the working age population in the top five percent of the income distribution, and the death rate) or disamenities (cost of living, crime and unemployment rates). These variables are commonly included in studies of elderly migration (Conway and Rork (2004), Bakija and Slemrod (2004), Conway and Rork). Within this set of exclusion restrictions, several of the expenditure variables, the crime rate, death rate, and the percentage of the working population in the top five percent of the income distri-

[32]Other exogenous predictors of the estate tax rate included in Conway and Rork (2006) were omitted from my instrument set as they would likely have a direct effect on the tax base (i.e. the income and sales tax measures).

bution are statistically significant. Finally, the tax rate set by neighboring jurisdictions is instrumented with the weighted set of neighbor characteristics ($\sum_{i \neq j}^{48} \omega_{ijt} X_{jt}$) as suggested in Kelijan and Prucha (1998) - a common approach in the literature (see Figlio et al 1999, Beasley and Case 1995, and Conway and Rork (2004) for single equation applications and Brett and Pinske 2000 for a simultaneous equation application).

### 4.5 Data

To estimate the model given by equation 3, I assemble a ten year panel for the forty-eight contiguous states covering the period 2001 through 2010. The following section details the data strategy used to measure the estate tax base ($M_{it}$), the estate tax rate ($T_{it}$), and all covariates included in the model.

#### 4.5.1 Measuring the Tax Base

Measuring the estate tax base with complete accuracy is not feasible. As noted in (Brulhart and Parchen 2010), taxpayers themselves cannot know the incidence of the estate tax as it depends on both the timing of their death and the value of their assets at that time. The literature has gotten around this hurdle by focusing on measures of the elderly (Conway and Houtenvill 2003, Conway and Rork 2006,) the wealthy elderly (Brulhart and Parchen 2010, Conway and Rork 2012), or the number of estates filed (Bakija and Slemrod (2004)) as the tax bases most likely to respond to changing estate tax policies. Along these lines, I implement three alternative measures of the tax base (M)

**(M1)** The number of estate tax returns filed in each state over the number of adult deaths in the state (population age forty-five and older).

**(M2)** The share of the state population age sixty-five and older in the top five percent of the income distribution

**(M3)** The share of the state population age sixty-five and older in the top twenty percent of the income distribution

Measure (M1) is constructed from estate tax filing data provided by the Statistics of Income division of the Internal Revenue Service (IRS). I select the return data tabulated by filing year rather than year to death because it is available every year rather than in three year intervals.[33] In order to obtained a scaled measure of this base, I divide the number of returns filed in each state by the number of deaths occurring in the population aged forty-five and older. Measure M2 and M3 are stock measures of the elderly population belonging to different income classes constructed from the American Community Survey.[34] Measure (M2) captures the stock of elderly residents with the highest income, and presumably, the highest probability of paying estate taxes. However, because it is possible for retired individuals to have substantial wealth without having income in the top five percent of the income distribution, I also consider elderly individuals with income in the top twenty percent of the income distribution.[35] I would expect to find this base the least responsive to the estate tax rate given that most are not impacted by the tax. They could however, as an important political base, have an impact on the estate tax policy selected by the state.

### 4.5.2 Tax Rate Definition

Because of the progressive nature of state estate tax schedules, the varying exemption levels across states, and the fact that rate schedules can vary by the relationship of the heir to the decedent, it is hard to arrive at one measure of a state's estate tax rate. While one might be inclined towards a measure like the top statutory rate for its visibility, such a measure would

[33]Federal estate tax returns are required to be filed within nine months of a decedent's death. However, 6-month extensions are commonly requested and granted. According to the IRS over ninety-nine percent of returns are filed within the second calendar year following the death.

[34]In an earlier version of this analysis, measure M2 and M3 were constructed from the Annual Social and Economic Supplement of the Current Population Survey (CPS). The move to the American Community Survey was motivated by the larger sample size. Results for the variables constructed from both sources were very similar.

[35]Income limits for the top twenty and top five percent are pulled form historical income tables produced by the Census and are available online at http://www.census.gov/hhes/www/income/data/historical/household/ .

not capture the large variations in the exemption levels set by states. Also, of the states that chose to decouple from federal law, most still follow the the old credit for state death taxes schedule which implements a top rate of sixteen percent.[36] The literature has addressed the measurement of state estate tax burdens in several ways. Conway and Rork (2004) implemented a measure based on estate tax revenue as their main measure of the estate tax while several others (Bakija and Slemrod 2004, Conway and Rork (2006), Brülhart and Parchet (2010)) have relied on some kind of estimated average or effective tax rate. For my analysis I choose to adopt an effective tax rate measure constructed for each state using the sum of the state and federal estate (and inheritance) tax burden that would result for a hypothetical taxable estate worth five million dollars in 2001. These calculations are made taking into consideration the deductibility of state estate taxes from the federal taxable estate introduced in 2005. For states imposing inheritance taxes, the exemption and marginal tax rates are a function of the heirs relationship to the decedent (spouse, lineal decedent, sibling, nephew, etc). When relevant, I make all inheritance calculations assuming the estate was left equally divided between two children.

Control variables

The control variables selected for the tax base and tax rate equations attempt to control for the economic, fiscal, demographic, and political factors which influence the locational decisions of seniors (in the case of the base equation) and a state's estate tax policy (in the case of the rate equation).

### 4.5.3 Estate Tax Base Equation

Certain amenities such as low rates of crime and unemployment, generous state spending on health and hospitals, and a low cost of living are generally believed to attract mobile se-

[36] States imposing top statutory rates other than sixteen percent include Tennessee, Washington, Pennsylvania, Ohio, Connecticut, Nebraska, and Kansas.

niors and are thus controlled for in the tax base equation. Similarly, seniors are thought to be deterred from locating in states with high taxes or spending on public goods that they are unlikely to consume (education for instance). More specifically, the fiscal variables controlled for in the model include last year's state per capita spending on welfare, education, health and hospitals, and highways as well as last year's revenue reliance on the sales, income, property and corporate tax bases (defined as the revenue generated from each source over general revenue). These variables are constructed from data obtained from the Census of Governments (COG) database. They are included in their lagged form to avoid possible endogeneity concerns.

A last fiscal variable that warrants discussion is a variable developed to capture the income tax breaks that many states offer to their senior residents. States often choose to grant age related tax benefits to the elderly. These benefits are typically applied to those aged sixty-five and older and come in several forms including the exemption of social security benefits or pension income from taxation and additional standard deductions or exemptions.[37] Because these tax advantages can be quite valuable to elderly households, especially wealthy ones, it is important to include a measure that reflects these state specific tax breaks. To obtain such a measure I use the NBER's TAXSIM calculator and data from the Current Population Survey (CPS) to construct the tax liability faced by a representative "high income" senior and non-senior household with the same total income. A variable I call "senior burden" is then constructed as the ratio of the senior tax burden to the non-senior tax burden. This ratio will be lower in states granting more favorable treatment tax treatment to seniors. The methodology used to construct the state by year panels of income data for the representative senior and non-senior households along with the methodology for obtaining their tax burdens is outlined in detail in Appendix A3.

Because states with a large populations of elderly will have high death rates, this variable is also included to help control for factors that make certain states more attractive to

[37] See Conway and Rork (2008) for a detailed discussion of these tax provisions and their evolution over the past several decades.

the elderly. A final demographic variable controls for the share of the state's working age population with income in the top five percent of the national income distribution. As noted in Bakija and Slemrod (2004), this variable will represent the prevalence of wealthy people in a state (or the potential estate tax base) and also capture unobserved amenities that draw the high-income to particular states. Last, state fixed effects are included to capture potentially important time invariant state specific factors such as climate.

### 4.5.4 Estate Tax Rate Equation

To isolate the impact of a state's own tax base and tax competition on the state's policy choice, I include controls for a state's political, economic, and demographic factors also suspected to exert influence estate tax policy. Because wealthier states will likely have larger potential estate tax bases, I include state per capita personal income in the model. Employment per capita is also included. With the political divide over estate tax policy being so partisan in nature, one would suspect the political makeup of the state to also be quite important in the determination of estate tax policy. To account for these factors I include two political controls, the first is an indicator for having a Democratic governor and the second is an indicator for a Republican majority in both the state senate and house. For demographics I follow Conway and Rork (2004) and include the percentage of the population age sixty-five and older and age eighty and older. This division is motivated in part because the young seniors may be both more geographically mobile and politically active and thus able to exert more influence on estate tax policy. Alternatively, the older seniors are more closely related to the true estate tax base.

The fiscal climate in a state is captured by the state debt per capita, per capita federal transfers received by the state, and the same basic set of tax variables included in the tax base equation (revenue reliance on the sales, income, property and corporate tax bases). Table 4.1 presents summary statistics for all variables included in the analysis.

## 4.6 Empirical Findings

Table 4.2 contains the estimation results for two equation model given by (3) when the definition of "neighbor" is based on geography. The results for the tax base equation are presented in the top panel of the table with the corresponding tax rate equation results presented beneath them. Each of the three columns contains estimates for one of the three alternative state estate tax base measures (estates filed, percentage of the senior population in the top five percent, and the percentage of the senior population in the top twenty percent). The Hansen J-test of overidentifying restrictions is also presented for each model. Appendix table A.3.2 contains the first-stage F-tests for instrument validity. The null hypothesis that the instruments are jointly equal to zero is rejected for all but one specification. Table 4.3 maintains the same setup but presents the results when the definition of neighbors is changed to the migration based weighting scheme.

Under the first weighting scheme, when the estate tax base is defined using the measure based on estates filed (M1), I find that a state's own tax rate has a small negative effect on the size of its tax base while the tax rates in neighboring states have a small positive effect. Specifically, a 10 percent increase in a state's own tax rate will lead to a reduction of the estate tax base by roughly 1.5 percent. Similarly, a 10 percent increase in the average tax rate imposed by a state's neighbors will lead to an increase in that state's own tax base of roughly 1.4 percent. The results for these same parameters when the tax base is defined as the percentage of state's senior population with income in the top five percent of the national income distribution, (M2), parallel these findings though their magnitudes are reduced. A 10 percent increase in a state's own tax rate now leads to a reduction of the estate tax base by roughly .5 percent while an increase in the average tax rates set in surrounding states will lead to an increase in the own state tax base of roughly 1.7 percent. Together, these results are consistent with the predictions laid out in the empirical framework and support the notion that a state's estate tax base is responsive to both its own state policy and the policies employed in surrounding states. Last, when moving to the broadest measure of the potential estate tax base - seniors with income in the top twenty percent - no evidence is detected to suggest this base responds to its own state's estate tax policy. This finding is not surprising given that under 2 percent of households actually leave taxable estates. Nevertheless, investigating this measure of the base has value in that it provides a chance to capture any households that will likely have taxable estates but were missed with the first two measures. More importantly, the finding that this base is unresponsive also helps rule out the possibility that the previous finding were spurious. Interestingly, there is some evidence suggesting that a state surrounded by high tax neighbors may experience some growth in their tax base. When switching to the migration weighting scheme (see top panel of Table 4.3), similar patterns are detected with some key differences. Specifically, a states own estate tax rate still appears to have a negative influence on the first two measures of its own estate tax base with very similar parameter magnitudes. However, a positive response by a state's own tax base is no longer detected as “neighbor's” increase their tax rates. This finding could be explained by the fact that migration based neighbors are not necessarily the surrounding states making it less likely that the tax base leaving these neighbors will spill into a state's own borders .

As expected, the size of a state's working population in the top five percent of the income distribution and a state's death rate have a positive influence on the size of the estate tax base. This reflects the fact that states offering certain amenities and opportunities that appeal to the high income or elderly will naturally have a larger estate tax base. When it comes to government expenditures, results are a bit more mixed. Spending on education and highways was sometimes found to have a positive relationship with the size of the estate tax base. Though one might expect the elderly to avoid states with relatively higher spending on education, this finding cold be explained by the fact that the high income elderly continue to value a higher level of public goods or that they are not as sensitive to government spending considerations compared to the general elderly population. This conjecture is supported by the fact that the coefficients on these variables are only significant for the first two more narrowly defined measures of the estate tax base and sometime flip signs for the third measure (M3). In some cases expenditure on welfare was found to have its expected negative effect on the size of the estate tax base though a positive impact was detected in one instance. In the case of additional taxes, it appears a state's estate tax base is negatively influence by reliance on income taxation and positively influenced by reliance on sales and property taxation while reliance on corporate taxation appears to have no discernible impact. Lastly, the variable capturing income tax breaks granted to seniors takes its expected negative sign across the different specifications though it is not statistically significant. This is not surprising giving that past research has not been able to detect an impact of these fiscal policies on the location of seniors (see Conway and Rork (2008, 2012).)

When moving to the corresponding tax rate equation, some evidence is found suggesting a state's estate tax base has a negative influence on the state's tax rate. As in the case of the tax base equation, this finding only holds up under the first and second definition of the tax base. Specifically It appears that a one percent increase in a states estate tax base results in a drop in the estate tax rate of roughly . 4-.6 percent, depending on the base definition. Though these findings are only marginally significant they do provide support for the hypothesis that a growing estate tax base may be able to exert more political influence to achieve policy goals. Alternatively, a growing estate tax base could allow a state to cut its effective tax rate (through either a cut in the marginal tax rate or and increase in the exclusion amount) and still maintain a given revenue level.

When considering how a state's estate tax rate reacts to those set in neighboring jurisdictions, I find a 10 percent cut in the estate tax rate in neighboring states leads to a 5.2 percent cut in the own state rate when the base definition is estates filed. Similar responses of 4.6 percent and 4 percent are detected under the two alternative estate tax base definitions. The results presented in Table 4.3 (when neighbors are based on the migration definition) again tell a similar story though their coefficients are slightly larger. Specifically, I now find a 10 percent cut in the estate tax rate of neighboring states leads to a 7.8 percent cut in the own state rate. The pattern that the coefficients diminish in magnitude as the base definition is made broader also continues to hold. The estimated magnitude of a states response to it's neighbors estate tax rate falls within the range of estimates produced by Conway and Rork (2004) in their study of estate tax competition and also display the same patter that the response is stronger under the migration based weighting scheme.

As one would expect, states with democratic governors were found to have higher estate tax rates while states with republican majorities in both the house and senate were found to have lower tax rates. States with larger "young" elderly populations (those aged sixty-five and up) were found to have higher estate tax rates while states with larger "old" elderly populations (aged eighty and up) were found to have lower rates. Tax rates were also lower in states that relied on only pick portion of the tax as opposed to those that implemented stand alone tax systems. States relying more heavily on sales and property taxes also had larger tax rates.

## 4.7 Conclusion

The aging of the population has spurred a new interest in the fiscally induced migration of retirees, especially with respect to estate/inheritance tax policy. This interest in state estate and inheritance taxes has been augmented by the numerous estate tax policy changes occurring over the last decade. In the past, evidence that the states strategically set their estate taxes in a manner consistent with tax competition has been clearly documented, both empirically and anecdotally. Interestingly though, evidence that the estate tax bases actually responds to any interstate differentials in these tax policies has been much more fleeting. The 2001 EGTRRA legislation which repealed the state death tax credit thus exacerbating interstate differentials and inducing a string of policy changes in estate taxation has created a unique opportunity to reinvestigate these matters.

Using a new framework which allows for the simultaneous determination of a state's tax base and rate while also considering the influence of neighbor states policies, I provide new evidence on both strategic state behavior and the mobility and influence of the estate tax base. When the estate tax base is fairly narrowly defined by focusing on actual estates filed in a state or the senior population with income in the top five percent of the income distribution, evidence is found suggesting that the estate tax base is mildly responsive to both changes in own state tax policy and the tax policy of neighbors. This result goes away once a wider potential estate tax base, such as seniors with income in the top twenty percent of the income distribution or all seniors. These findings line up with the findings of Bakija and Slemrod (2004) who demonstrated that high state estate and inheritance taxes have a modest negative impact on estates filed within a state as well as the findings of Conway and Rork (2006, 2012) who found high state estate and inheritance taxes did not have an impact of the migration of the broader elderly population or those falling into the top twenty-five percent of the income distribution. The responsiveness of the estate tax base documented here also helps confirm that tax competition is a true factor behind the observed strategic estate tax policy setting behavior. However, the small mobility effects documented here are not enough to explain strong tax cutting responses of states to changes in their neighbor's estate tax policies and the decisions of many states to abandon this tax base entirely. Political factors must also surely play an important role in a states estate tax policy choice and some evidence found here suggests a growing estate tax base may be able to apply downward pressure to taxes they find unfavorable.

While the past decade has witnessed both the inception and repeal of state estate taxes, the trend emerging towards the end of the period appears in favor of repeal. There are of course several exceptions such as Hawaii, who chose to enact a new tax in the year that the federal estate tax was temporarily repealed and Connecticut who recently retroactively lowered their exemption level. The future may yet hold even more action in the state estate tax arena given that the ARTA (2012) legislation has settled any uncertainty surrounding the return of the state death tax credit. This news apparently surprised several states including California, Colorado, and New Mexico who had included pick-up tax revenue in their multi- year budget estimates. Whether these revenue hungry states will react by reinstating their estate taxes remains to be seen as does the behavior of the remaining states with estate taxes still intact. What does seem clear is that these policy decisions will be influenced by the relevant tax bases and will not be made in isolation from the policy choices in neighboring states.

**Figure 4.1 Coefficient of Variation: Estate Tax Revenue as % of Total State Revenue**

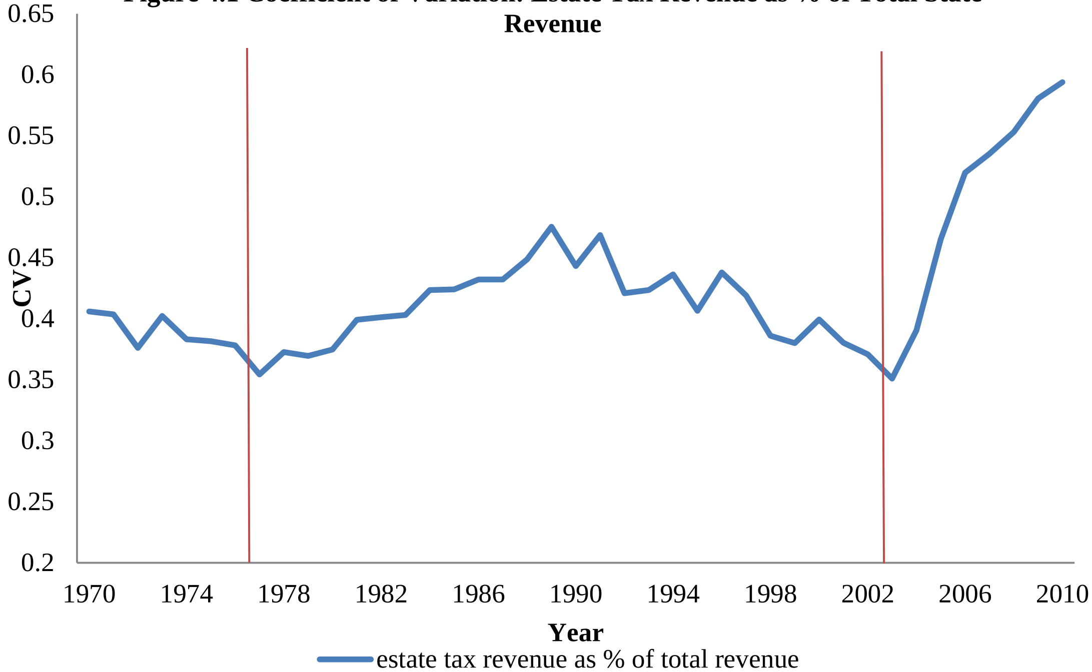


**Figure 4.2 Federal Estate Tax Schedule**

| Year | Exclusion Amount | Top Tax Rate |
|---|---|---|
| 2001 | $675,000 | 55% |
| 2002 | $1 million | 50% |
| 2003 | $1 million | 49% |
| 2004 | $1.5 million | 48% |
| 2005 | $1.5 million | 47% |
| 2006 | $2 million | 46% |
| 2007 | $2 million | 45% |
| 2008 | $2 million | 45% |
| 2009 | $3.5 million | 45% |
| 2010 | repealed | |
| 2011 | $5 million | 35% |
| 2012 | $5.12 million | 35% |
| 2013 | $5.25 million | 40% |

**Figure 4.3 Estate Tax Payable by a $3,000,000 Estate in Pick-Up Only State**

| Year | Total Estate Tax | State Share | Federal Share |
|---|---|---|---|
| 2001 | 1,070,250 | 182,000 | 888,250 |
| 2002 | 930,000 | 136,500 | 793,500 |
| 2003 | 925,000 | 91,000 | 834,000 |
| 2004 | 705,000 | 45,500 | 659,000 |
| 2005 | 695,000 | 0 | 695,000 |
| 2006 | 460,000 | 0 | 460,000 |
| 2007 | 450,000 | 0 | 450,000 |
| 2008 | 450,000 | 0 | 450,000 |
| 2009 | 0 | 0 | 0 |
| 2010 | 0 | 0 | 0 |
| 2011 | 0 | 0 | 0 |

This table is adopted from Cooper et al. (2004) and is updated cover 2011 law.

**Figure 4.4 Federal Net Estate Tax Collected vs. State Death Tax Cedit/Deduction Paid**

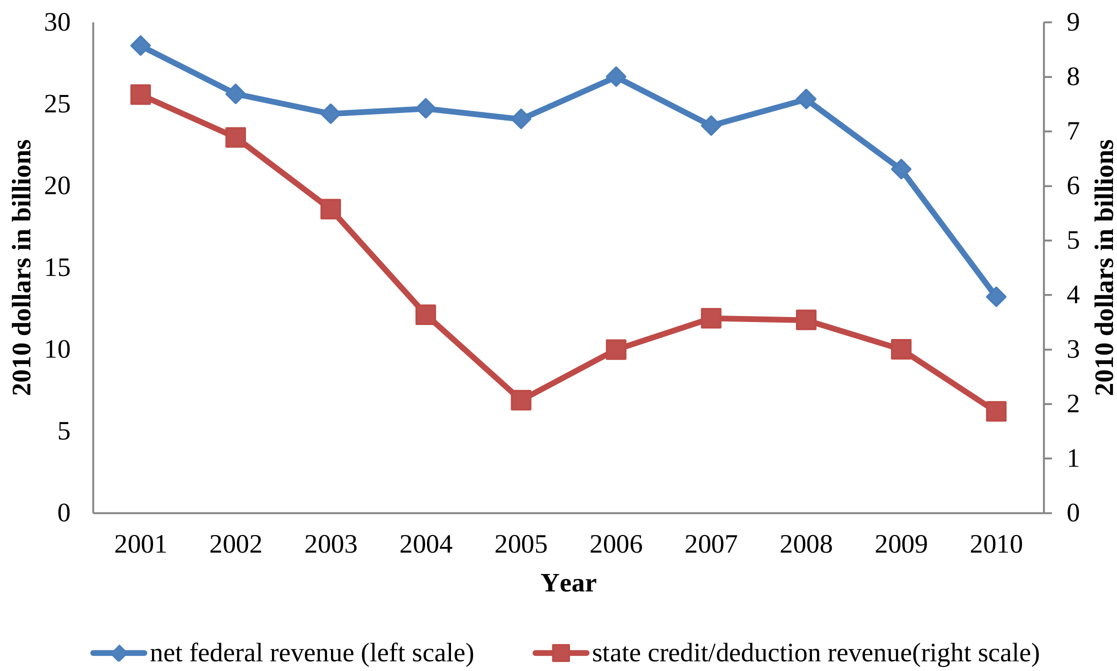

**Figure 4.5. Percentage of States Collecting Only the Pick-Up Tax**

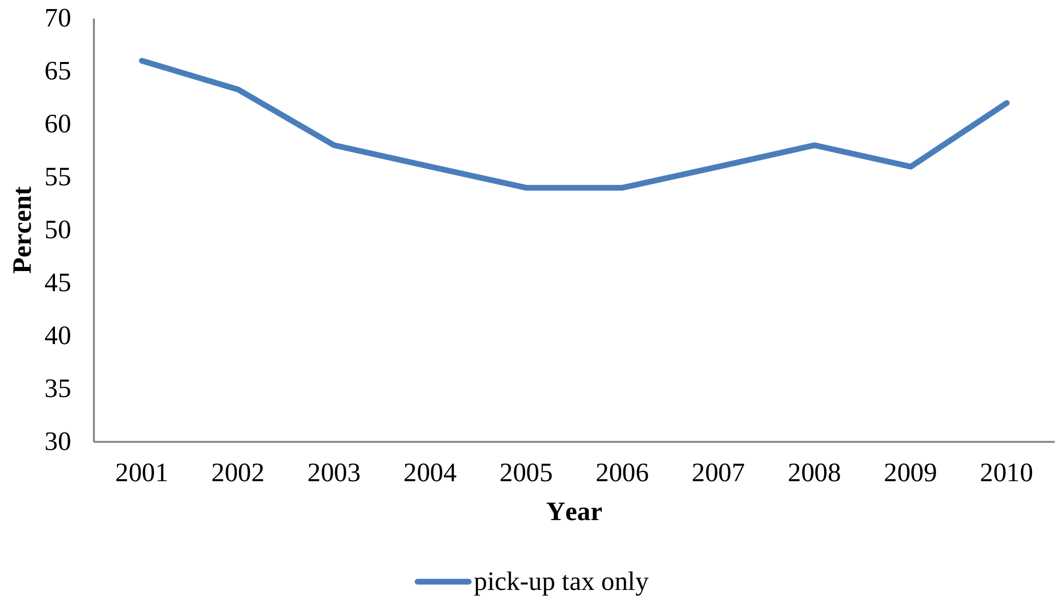


**Figure 4.6 Federal and State Estate Tax Gap**

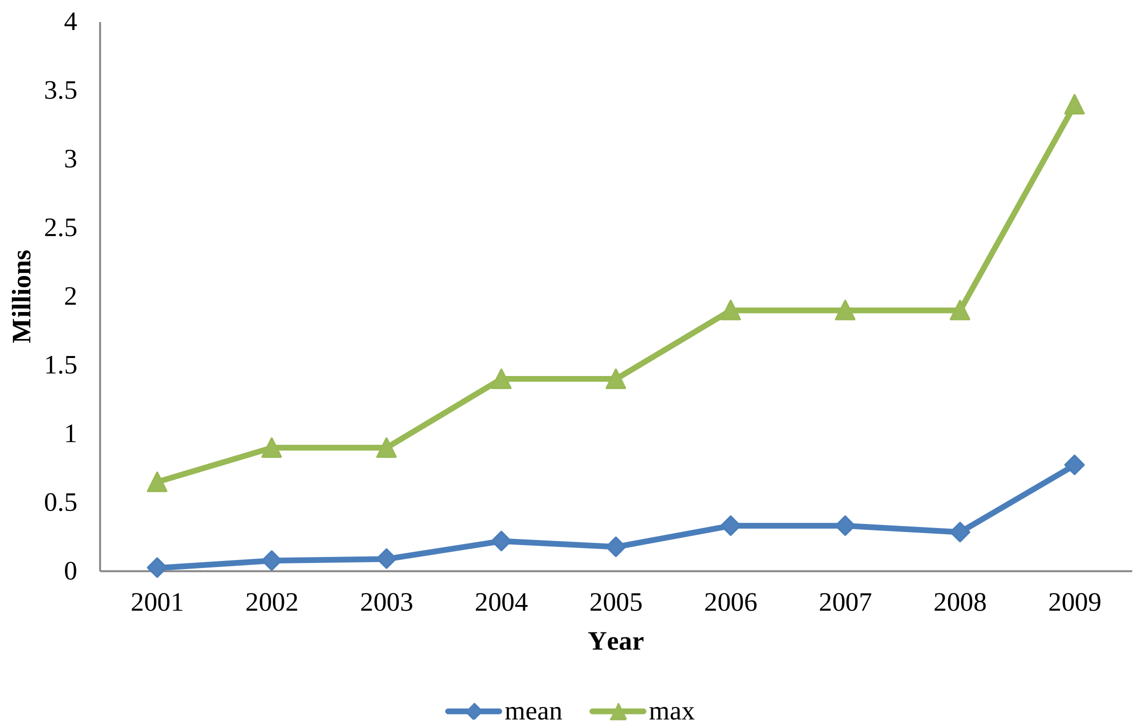


Table note: for 2010 the federal exclusion amount was unlimited. I therefore do not calculate the federal-state gap for that year.

**Table 4.1 Summary Statistics (2001-2010)**

| Economic and Demographic Variables | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|
| State employment | 0.482 | 0.034 | 0.384 | 0.553 |
| Per capita personal income | 38.144 | 5.677 | 27.696 | 58.831 |
| Population (in thousands) | 6136.291 | 6571.439 | 494.657 | 37349.360 |
| **Percent of Population** | | | | |
| Age 65 & older | 0.126 | 0.016 | 0.082 | 0.174 |
| Age 80 & older | 0.034 | 0.007 | 0.019 | 0.053 |
| **Political Variables** | | | | |
| Democratic governor (yes=1) | 0.513 | 0.500 | 0.000 | 1.000 |
| Republican majority (yes=1) | 0.327 | 0.470 | 0.000 | 1.000 |
| **Amenities** | | | | |
| Crime rate (per 100 residents) | 3.656 | 0.909 | 1.946 | 6.404 |
| % of working population in top 5% | 0.059 | 0.026 | 0.023 | 0.141 |
| Median home price index ($1000s) | 157.83 | 65.29 | 73.11 | 479.66 |
| Unemployment rate | 5.66 | 2.009 | 2.7 | 14.9 |
| Death rate | 0.008 | 0.001 | 0.005 | 0.011 |
| Senior Tax Burden | 0.905 | 0.016 | 0.851 | 0.935 |
| **Fiscal Variables** | | | | |
| State per capita debt | 6.923 | 2.200 | 3.087 | 15.473 |
| State per capita transfers | 1.654 | 0.488 | 0.755 | 4.297 |
| **State and Local Government Per Capita Expenditures by Category (in $1000s)** | | | | |
| Health & Hospital | 0.595 | 0.274 | 0.143 | 2.276 |
| Welfare | 1.248 | 0.351 | 0.317 | 2.476 |
| Education | 2.558 | 0.38 | 1.76 | 4.461 |
| Highway | 0.549 | 0.166 | 0.295 | 1.349 |
| **Other Taxes as Share of General Revenue** | | | | |
| Property tax share | 0.159 | 0.057 | 0.062 | 0.359 |
| Sales tax share | 0.124 | 0.054 | 0 | 0.267 |
| Income tax share | 0.111 | 0.061 | 0 | 0.248 |
| Corporate tax share | 0.018 | 0.012 | 0 | 0.07 |
| **Estate Tax Base Variables** | | | | |
| Percentage of seniors with income in top 5 % | 0.027 | 0.011 | 0.003 | 0.06 |
| Percentage of seniors with income in top 20% | 0.089 | 0.026 | 0.034 | 0.172 |
| Estates filed to adult deaths | 0.023 | 0.015 | 0.002 | 0.095 |
| **Estate Tax Rate Variables** | | | | |
| Total state and federal effective rate for 5 million dollar estate | 0.296 | 0.104 | 0 | 0.452 |
| Top state rate | 0.099 | 0.076 | 0 | 0.19 |
| Pickup only state | 0.569 | 0.496 | 0 | 1 |

**Table 4.2 Estimation Results for Estate Tax Base and Rate Equation, Weight Matrix is WI**

| **Tax base equation:** | | | | | | |
|---|---|---|---|---|---|---|
| Tax base measure is: | Base M1 | | Base M2 | | Base M3 | |
| effective tax rate | -0.152*** | (0.028) | -0.050** | (0.023) | -0.006 | (0.032) |
| neighbor's tax rate | 0.147* | (0.089) | 0.172** | (0.070) | 0.181* | (0.098) |
| crime rate (per 100 residents) | 0.002** | (0.001) | 0.002** | (0.001) | -0.000 | (0.002) |
| % of working population in top 5% | -0.073 | (0.072) | 0.234*** | (0.072) | 0.383*** | (0.116) |
| unemployment rate | -0.000 | (0.000) | 0.000 | (0.000) | -0.001** | (0.001) |
| death rate | 0.865 | (2.072) | 4.194** | (1.891) | 6.111* | (3.188) |
| median home price | -0.000 | (0.000) | 0.000 | (0.000) | -0.000 | (0.000) |
| senior tax burden | -0.043 | (0.081) | 0.007 | (0.077) | -0.128 | (0.120) |
| last year's expenditure on health | -0.013*** | (0.005) | -0.003 | (0.004) | 0.004 | (0.006) |
| last year's expenditures on welfare | -0.010*** | (0.002) | 0.004* | (0.002) | 0.003 | (0.004) |
| last year's expenditure on education | 0.003 | (0.002) | 0.005* | (0.003) | 0.002 | (0.004) |
| last year's expenditure on highways | 0.008** | (0.004) | 0.007* | (0.004) | -0.007 | (0.006) |
| last year's property tax share | -0.037 | (0.037) | 0.057* | (0.031) | .121*** | (0.044) |
| last year's sales tax share | 0.039 | (0.042) | 0.099** | (0.042) | 0.188*** | (0.051) |
| last year's income tax share | -0.114*** | (0.037) | 0.042 | (0.026) | 0.055 | (0.039) |
| last year's corporate tax share | 0.039 | (0.073) | 0.026 | (0.061) | 0.103 | (0.092) |
| **Tax rate equation:** | | | | | | |
| tax base | -0.436* | (0.254) | -0.559* | (0.299) | -0.161 | (0.305) |
| neighbor's tax rate | 0.522** | (0.228) | 0.458** | (0.227) | 0.395* | (0.225) |
| state per capita debt | 0.000 | (0.001) | -0.000 | (0.002) | -0.000 | (0.001) |
| state per capita transfers | 0.000 | (0.003) | -0.000 | (0.003) | -0.001 | (0.003) |
| state employment | 0.063 | (0.111) | 0.025 | (0.112) | 0.028 | (0.117) |
| per capita personal income | 0.001 | (0.001) | 0.001 | (0.001) | 0.001 | (0.001) |
| democratic governor (yes=1) | 0.003 | (0.002) | 0.002 | (0.002) | 0.004* | (0.002) |
| republican majority | -0.004* | (0.002) | -0.001 | (0.003) | -0.001 | (0.003) |
| % population 65 & up | 0.800** | (0.337) | 0.941*** | (0.365) | 0.821** | (0.377) |
| % population 80 & up | -1.260** | (0.505) | -1.017* | (0.524) | -1.018* | (0.557) |
| Pickup tax only (yes =1) | -0.040*** | (0.005) | -0.042*** | (0.005) | -0.046*** | (0.005) |
| population | 0.000 | (0.000) | 0.000 | (0.000) | 0.000 | (0.000) |
| last year's property tax share | 0.166* | (0.090) | 0.091 | (0.086) | 0.120 | (0.085) |
| last year's sales tax share | 0.141 | (0.089) | 0.233** | (0.105) | 0.192* | (0.114) |
| last year's income tax share | -0.094 | (0.093) | -0.043 | (0.096) | -0.021 | (0.094) |
| last year's corporate tax share | -0.069 | (0.183) | 0.012 | (0.190) | -0.089 | (0.198) |
| | | | | | | |
| Hansen's J-test | 61.429 | | 48.966 | | 43.281 | |
| p-value | 0.037 | | 0.214 | | 0.416 | |
| Observations | 480 | | 480 | | 480 | |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All models include state and year fixed effects.

**Table 4.3 Estimation Results for Estate Tax Base and Rate Equation, Weight Matrix is WII**

| **Tax base equation:** | | | | | | |
|---|---|---|---|---|---|---|
| Tax base measure is: | Base M1 | | Base M2 | | Base M3 | |
| effective tax rate | -0.153*** | (0.025) | -0.038** | (0.019) | 0.016 | (0.031) |
| neighbor's tax rate | 0.138 | (0.153) | -0.011 | (0.133) | 0.220 | (0.205) |
| crime rate (per 100 residents) | 0.001 | (0.001) | 0.002** | (0.001) | 0.000 | (0.002) |
| % of working population in top 5% | -0.008 | (0.070) | 0.255*** | (0.073) | 0.428*** | (0.108) |
| unemployment rate | 0.000 | (0.000) | 0.000 | (0.000) | -0.001 | (0.001) |
| death rate | -0.001 | (1.733) | 2.041 | (1.747) | 3.769 | (2.907) |
| median home price | -0.000 | (0.000) | 0.000** | (0.000) | -0.000 | (0.000) |
| senior tax burden | -0.006 | (0.064) | -0.061 | (0.056) | -0.060 | (0.085) |
| last year's expenditure on health | -0.014*** | (0.004) | -0.004 | (0.004) | 0.001 | (0.005) |
| last year's expenditures on welfare | -0.011*** | (0.002) | 0.003 | (0.002) | 0.001 | (0.004) |
| last year's expenditure on education | 0.003 | (0.002) | 0.007*** | (0.003) | 0.003 | (0.004) |
| last year's expenditure on highways | 0.007** | (0.004) | 0.006 | (0.004) | -0.007 | (0.006) |
| last year's property tax share | -0.065* | (0.039) | 0.046 | (0.033) | 0.066 | (0.044) |
| last year's sales tax share | 0.051 | (0.040) | 0.111*** | (0.039) | 0.195*** | (0.051) |
| last year's income tax share | -0.123*** | (0.035) | 0.016 | (0.028) | 0.015 | (0.040) |
| last year's corporate tax share | -0.016 | (0.067) | 0.048 | (0.059) | 0.111 | (0.092) |
| **Tax rate equation:** | | | | | | |
| tax base | -0.740*** | (0.208) | -0.491 | (0.322) | 0.172 | (0.313) |
| neighbor's tax rate | 0.782** | (0.379) | 0.545 | (0.389) | 0.654* | (0.370) |
| state per capita debt | 0.000 | (0.001) | 0.000 | (0.001) | -0.000 | (0.002) |
| state per capita transfers | -0.000 | (0.003) | -0.001 | (0.003) | -0.000 | (0.003) |
| state employment | -0.007 | (0.103) | -0.047 | (0.113) | -0.106 | (0.114) |
| per capita personal income | 0.001 | (0.001) | 0.002** | (0.001) | 0.001** | (0.001) |
| democratic governor (yes=1) | 0.001 | (0.002) | 0.002 | (0.002) | 0.003 | (0.002) |
| republican majority | -0.001 | (0.002) | -0.001 | (0.003) | -0.001 | (0.003) |
| % population 65 & up | 0.529 | (0.331) | 0.867** | (0.366) | 0.605 | (0.384) |
| % population 80 & up | -0.543 | (0.485) | -0.661 | (0.516) | -0.452 | (0.547) |
| Pickup tax only (yes =1) | -0.037*** | (0.005) | -0.044*** | (0.005) | -0.046*** | (0.005) |
| population | 0.000 | (0.000) | 0.000* | (0.000) | 0.000 | (0.000) |
| last year's property tax share | 0.146 | (0.094) | 0.157* | (0.090) | 0.131 | (0.090) |
| last year's sales tax share | 0.163* | (0.093) | 0.264** | (0.104) | 0.165 | (0.109) |
| last year's income tax share | -0.047 | (0.098) | -0.014 | (0.098) | -0.010 | (0.094) |
| last year's corporate tax share | -0.112 | (0.178) | -0.126 | (0.178) | -0.260 | (0.186) |
| Hansen's J-test | 102.85 | | 69.389 | | 62.375 | |
| p-value | 0.000 | | 0.049 | | 0.022 | |
| Observations | 480 | | 480 | | 480 | |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All models include state and year fixed effects.

## 5 Conclusion

The three essays contained within this dissertation have sought to contribute to the body of knowledge examining how economic agents strategically respond to changes in both federal and state tax policy. While essays one and three focused on identifying strategic responses related to inter-state competition following federal reforms, essay 2 contributed to the literature examining how individuals change their income in response to changing marginal income tax rates.

The results from Essay 1 demonstrate that states appear highly responsive to multiple dimensions of welfare policy set in surrounding jurisdictions. More interestingly, evidence suggests that this strategic behavior associated with a 'race to the bottom' intensified in the wake of the 1996 reform. Additionally, the results demonstrate the methodological importance of considering policy dynamics when modeling interstate competition. Overall, the analysis paired recent state policy changes suggest we will likely see a continued reduction in the generosity of state welfare programs. This finding should be of interest to both those concerned with the TANF program and those studying other transfer programs considered possible candidates for further decentralization such as Medicaid and the SNAP program.

Essay 3 also studied interstate competition over policies aimed at redistribution, though for a very different population of people – the wealthy elderly. An interesting theme I found across my studies of both welfare competition and estate tax competition was the notion that states were seeming to react to the policy changes of their neighbors as if their populations were highly mobile even though a growing body of empirical evidence suggests otherwise. To more fully explore both inter-state estate tax competition and the mechanisms behind it, I developed a model in which the estate tax rate and base were simultaneously determined. This innovation helped to shed light on both the strategic policy behavior of states and the mobility of the estate tax base. The results indicating a states estate tax base is negatively influenced by its own tax rate and positively influenced by the tax rate set in neighboring jurisdictions may begin to build a small consensus in the literature that the very rich elderly are in fact sensitive to estate taxes though additional research will be required.

Lastly, Essay 2 provides an interesting set of results in which the elasticity of taxable income is subject to a new set of sensitivity analysis relating to heterogeneity across education attainment levels, selection on both observables and unobservables, identification, and tax rate definition. These analyses are made possible by the use of survey data (matched CPS panels) which contain richer demographic information than the standard tax-panel typically used in the ETI literature. The analysis concludes with a model in which a new arguablely more exogenous instrument is implemented. These preferred estimates put the ETI in a range of .4-.5, much higher than estimates obtained with the standard instrument strategy.

While the essays contained within this dissertation have each touched upon different aspects of the tax and transfer system ranging all the way from the TANF program serving the very poor to estates taxes impacting only the very wealthy, they have been tied together by the theme of working to better understand strategic responses to changes in tax and transfer policies. Enhancing our knowledge on the policy responses of both state governments and individuals can help contribute to the design of a more effective tax and transfer system.

# A Appendix

## A.1 Appendix for Chapter 2

### A.1.1 Data Appendix

To obtain state level estimates of the effective tax rates and effective benefit guarantees, I implement the reduced-form methodology of Ziliak (2007). This study used micro data from the AFDC Quality Control System (AFDC-QC) as well as the National TANF Data Reporting System (NTDS) to estimate effective tax rates and benefit guarantees for all states over the period 1983-2002. I simply extend his analysis to obtain results through 2008. The basic estimation equation is as follows

$$B_{ijt} = \alpha^0_{jt} + \alpha^1_{jt} K2_{ijt} + \alpha^2_{jt} K3_{ijt} - t^e_{jt} E_{ijt} - t^n_{jt} N_{ijt} + \epsilon_{ijt} \tag{16}$$

where $B_{ijt}$ is the actual monthly benefit amount received by individual i, in state j, at time t. The right hand side variables consist of controls for family size and income as these determine a recipients benefit level. Specifically, K2 is an indicator for the presence of two or more children and K3 equals the number of additional children present. E and N represent earned and unearned income respectively. Earned income is defined to be the sum of reported wages and salaries, self employment income, and any reported refunds from the Earned Income Tax Credit. Unearned income is defined to be the sum of income from social security, railroad retirement, Supplemental Security Income, food stamps, unemployment insurance, workers compensation, veterans benefits, child support, general assistance, housing assistance, education grants, and any other reported income.

As explained by Ziliak, the state-specific and time-varying intercepts $\alpha^0_{jt}$ reflect the effective benefit guarantee for a family of two while the sum $\alpha^0_{jt} + \alpha^1_{jt}$ reflects the effective guarantee for a family of three and so on. The coefficients $t^e_{jt}$ and $t^n_{jt}$ are the estimates of the effective tax rates. Rather than estimating the above equation with ordinary least squares (OLS), I follow Ziliak and use a truncated maximum likelihood estimator due to the truncated sample which results from the minimum statutory benefit. See Ziliak 2007 for more detail on estimation and selection criterion. Sample sizes were lowest in 1996 and 1997 during the transition from the AFDC-QC and NTDS. During this time and the next two years there were an increased number of states with missing data or data with insufficient variation to estimate the model parameters. To obtain a full time series for each state I use linear interpolation to fill in 16 missing parameter values.

### A.1.2 Additional Sensitivity Analysis

As previously discussed, the finite sample size of this analysis requires one to restrict the potential instrument set. Baseline estimates were obtained by instrumenting the spatial variable with its second through fourth lags collapsed. As a robustness check, Table A1 presents estimates for the full period static and dynamic models obtained with several alternative instrument choices (these include using more lags and starting with the third lag rather than the second). The top panel of the table contains to static spatial coefficient estimates while the the bottom panel contains the short run (SR) spatial coefficient estimates from the dynamic model as well as the calculated corresponding long run (LR) estimates. Point estimates appear fairly robust to alternative lag structures. The efficiency of different instrument sets appears to be more variable specific.

**Table A1.2.1 Sensitivity analysis of spatial coefficient to alternative instrument lag structures (full period )**

| Static Model | Maximum Benefit | Effective Benefit | ETR on Earned Income |
|---|---|---|---|
| 2nd through 3rd lags | 0.928** | .775** | 0.758*** |
| | (0.462) | (0.342) | (0.271) |
| 2nd through 4th lags | 0.926** | .745** | 0.779*** |
| | (0.420) | (0.290) | (0.241) |
| 2nd through 6th lags | 0.949** | .761*** | 0.661** |
| | (0.390) | (0.270) | (0.260) |
| 3rd through 5th lags | 0.965** | 1.037** | 0.702* |
| | (0.391) | (0.426) | (0.355) |
| 3rd through 7th lags | 0.880** | 1.016** | 0.678* |
| | (0.342) | (0.430) | (0.341) |
| 4th through 6th lags | 1.040** | 1.066 | 0.683** |
| | (0.408) | (0.783) | (0.326) |
| 4th through 8th lags | 0.976** | 1.049 | 0.682** |
| | (0.389) | (0.658) | (0.327) |

| Dynamic Model | SR | LR | SR | LR | SR | LR |
|---|---|---|---|---|---|---|
| 2nd through 3rd lags | 0.084 | .620 | 0.241* | .797** | 0.308* | .606* |
| | (0.112) | (.653) | (0.131) | (.315) | (0.169) | (.316) |
| 2nd through 4th lags | 0.095 | .667 | 0.234* | .777*** | 0.320** | .622** |
| | (0.110) | (.588) | (0.119) | (.292) | (0.165) | (.406) |
| 2nd through 6th lags | 0.083 | .542 | 0.281** | .920*** | 0.397*** | .732*** |
| | (0.428) | (2.373) | (0.136) | (.316) | (0.144) | (.264) |
| 3rd through 5th lags | 0.021 | .202 | 0.421* | 1.02*** | 0.349*** | .677** |
| | (0.110) | (.991) | (0.214) | (.354) | (0.171) | (.333) |
| 3rd through 7th lags | 0.0622 | .491 | 0.439* | 1.086*** | 0.445** | .823** |
| | (.113) | (.697) | (0.229) | (.375) | (0.169) | (.329) |
| 4th through 6th lags | 0.150 | .883 | 0.465* | 1.208*** | 0.449*** | .813*** |
| | (0.117) | (.613) | (0.236) | (.318) | (0.153) | (.289) |
| 4th through 8th lags | 0.132 | .894 | .434 | 1.243*** | 0.446** | .803*** |
| | (0.126) | (.744) | (0.243) | (.375) | (0.154) | (.286) |

Robust standard errors in parentheses. *** p<0.01, **P<0.05, *p<0.1. Only spatial coefficients are reported. SR denotes short run coefficients and LR denotes long run coefficients.

## A.2 Appendix for Chapter 3

### A.2.1 Summary Statistics for Matched and Repeated Cross Sections of CPS

**Table A2.1.1 Summary Statistics for Matched CPS data, 1979-2008**

| | Mean | Std. Dev |
|---|---|---|
| **Demographics** | | |
| Single | 0.18 | 0.39 |
| Female | 0.30 | 0.46 |
| White | 0.87 | 0.33 |
| African American | 0.08 | 0.28 |
| Other | 0.04 | 0.20 |
| Age | 41.44 | 9.42 |
| Less than High School | 0.12 | 0.33 |
| High School Graduate | 0.34 | 0.48 |
| More than High School | 0.53 | 0.50 |
| Child under 6 | 0.22 | 0.41 |
| Child under 18 | 0.41 | 0.49 |
| **Income and Tax Rates** | | |
| Broad Income (Year 1) | 70429.79 | 56460.08 |
| Taxable Income (Year 1) | 61157.47 | 54311.57 |
| Net-of-Tax Share (Federal+State) | 73.52 | 11.84 |
| Net of Tax Share (Federal+State+FICA) | 67.92 | 10.58 |

Observations 198,447. Sample is individuals with broad income greater than $10,000

**Table A2.1.2 Summary Statistics for Repeated Cross Section CPS data, 1979-2008**

| | Mean | Std. Dev |
|---|---|---|
| **Demographics** | | |
| Single | 0.20 | 0.40 |
| Female | 0.34 | 0.47 |
| White | 0.85 | 0.36 |
| African American | 0.10 | 0.30 |
| Other | 0.05 | 0.22 |
| Age | 40.95 | 9.71 |
| Child Under 6 | 0.22 | 0.42 |
| Child Under 18 | 0.41 | 0.49 |
| Less than High School | 0.14 | 0.34 |
| High School Graduate | 0.33 | 0.47 |
| More than High School | 0.53 | 0.50 |
| **Income and Tax Rates** | | |
| Broad income | 67944.51 | 58839.23 |
| Taxable income | 58734.21 | 56655.03 |
| Net-of-Tax Share (Federal+State) | 75.02 | 13.27 |
| Net of Tax Share (Federal+State+FICA) | 69.16 | 12.14 |
| **Labor Variables** | | |
| Hours | 1907.62 | 847.29 |
| Worker | 0.91 | 0.28 |
| Before-Tax Wage | 20.42 | 44.34 |
| After-Tax Wage | 13.34 | 27.51 |
| Non Labor Income ($1000s) | 26.60 | 39.19 |
| Virtual Non Labor Income ($1000s) | 32.68 | 40.41 |

462,869 observations. Sample is broad income greater than 10,000.

## A.2.2 Benchmark Specification Tests on Baseline ETI Model

**Table A2.2.1 Benchmark Specification Tests on Baseline ETI Model**

| | Unweighted | Time period 1979-1990 | Deciles for Initial Income Controls |
|---|---|---|---|
| Broad Income | | | |
| Fed + State | 0.003 | 0.168** | -0.009 |
| | (0.023) | (0.067) | (0.035) |
| Fed +State+ Fica | 0.010 | 0.085 | -0.088*** |
| | (0.019) | (0.052) | (0.027) |
| Taxable Income | | | |
| Fed + State | 0.044 | 0.214*** | -0.020 |
| | (0.036) | (0.081) | (0.043) |
| Fed +State+ Fica | 0.044 | 0.083 | -0.115*** |
| | (0.030) | (0.062) | (0.034) |

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. All regressions include controls for marital status and time effects for initial year. Income range is broad income greater than $10,000.

**Figure A3.1 Time line of estate tax policy changes, 2001-present**

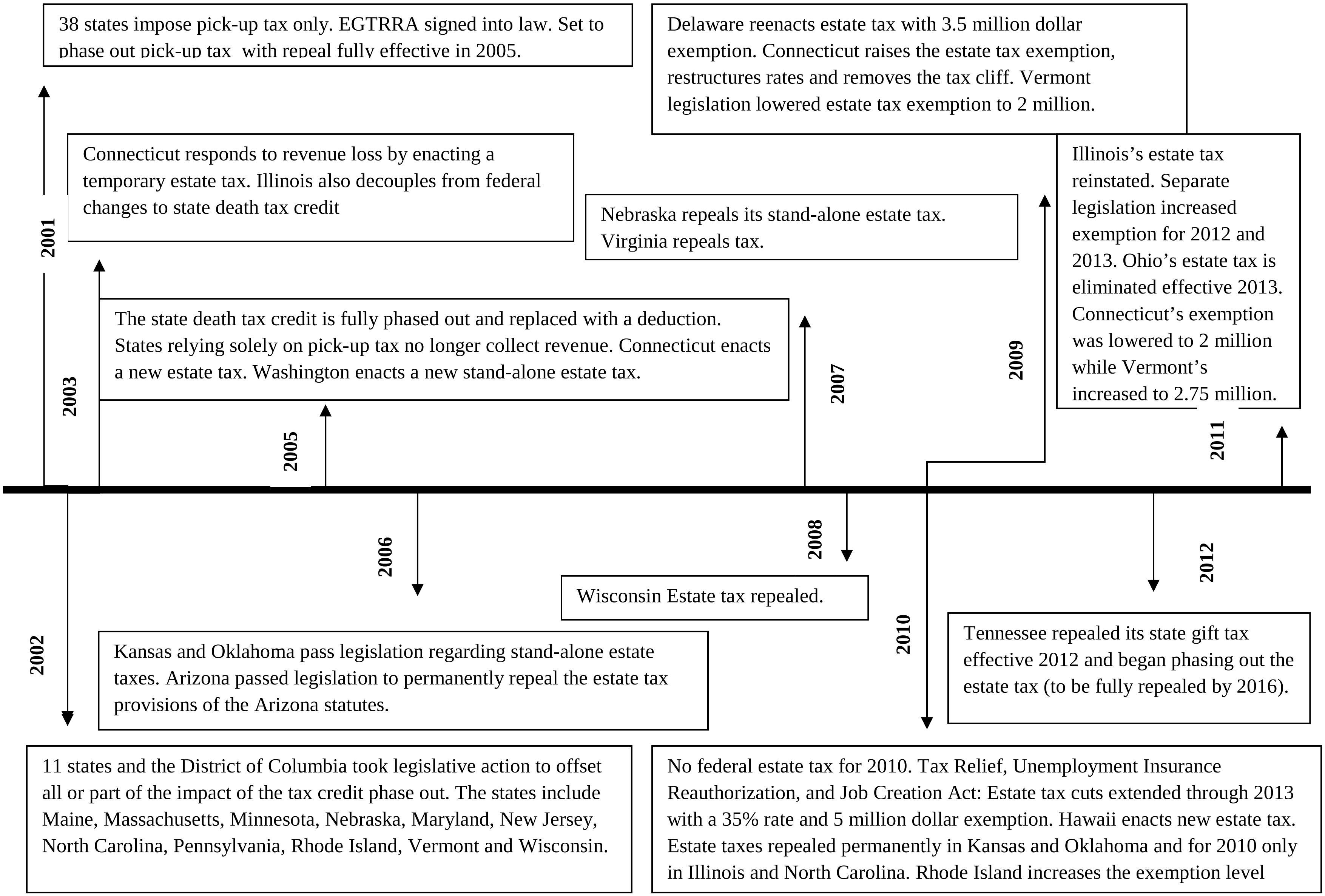

**Figure A3.2 Maximum Credit for State Death Taxes**

| Adjusted taxable estate equal to or more than | Adjusted taxable estate less than | Credit on amount in column (1) | Rate of credit on excess over amount in column (1) per (cent) |
|---:|---:|---:|---:|
| 0 | 40000 | 0 | 0 |
| 40000 | 90000 | 0 | 0.8 |
| 90000 | 140000 | 400 | 1.6 |
| 140000 | 240000 | 1200 | 2.4 |
| 240000 | 440000 | 3600 | 3.2 |
| 440000 | 640000 | 10000 | 4 |
| 640000 | 840000 | 18000 | 4.8 |
| 840000 | 1040000 | 27600 | 5.6 |
| 1040000 | 1540000 | 38800 | 6.4 |
| 1540000 | 2040000 | 70800 | 7.2 |
| 2040000 | 2540000 | 106800 | 8 |
| 2540000 | 3040000 | 146800 | 8.8 |
| 3040000 | 3540000 | 190800 | 9.6 |
| 3540000 | 4040000 | 238800 | 10.4 |
| 4040000 | 5040000 | 290800 | 11.2 |
| 5040000 | 6040000 | 402800 | 12 |
| 6040000 | 7040000 | 522800 | 12.8 |
| 7040000 | 8040000 | 650800 | 13.6 |
| 8040000 | 9040000 | 786800 | 14.4 |
| 9040000 | 10040000 | 930800 | 15.2 |
| 10040000 | and up | 1082800 | 16 |

Source: Internal Revenue Code

## Appendix A3.3 TAXSIM9 Estimated Senior Tax Break Appendix

**Step 1:** I extract data from the 2000 March CPS and create a senior sample (married households aged 65 and older) and a non-senior sample (married households aged 35 to 55). Each sample is then split into income quintiles and only the top quintile for each sample is retained (those with income over $113,476 for the non-elderly sample and those with incomes over $66,600 for the elderly sample).

**Step 2**: I then construct the mean income for each sample by the component categories needed by the TAXSIM calculator – earnings of the household head and their spouse, dividend income, interest and rent, pensions, social security benefits, unemployment compensation, and other income (which is treated as non-taxable). I use the mean values of the different income components in combination with the mean total sample income to construct estimates of the proportion of income the representative household in each sample receives from the various sources.

**Step 4:** Next I multiply $150,000 by the sample specific proportions so that each sample's representative high income household will have the same amount of total income but apportioned differently across the income components. See table A3.1.

**Step 3:** I then inflate the income values obtained for each sample from year 2000 data using the Personal Consumption Expenditure Index (PCE) to obtain income values for the same representative households for 2001-2011 (assuming income only grew at the rate of inflation).

**Step 4:** State by year panels of the senior and non-senior representative households are then constructed and run through the TAXSIM calculator. I enter zero for the number of taxpayers over 65 for the non-senior sample and two for the senior sample. The TAXSIM calculator will apply the age related tax breaks in the calculation of federal, and more importantly, state tax burdens. TAXSIM provides output on the estimated federal, state, and FICA tax burdens for each state-year observation for both the senior and non-senior samples.

**Step 5:** I then obtain the combined federal, state, and FICA estimate tax burdens for each state-year observation and sample and define my final variable, Estimated Senior Tax Break, as the total senior tax burden over the total non-senior tax burden.[1]

[1] The individual is assumed to only bear the employee's share of the FICA tax.

**Table A3.1 Construction of representative high-income senior and non-senior household**

| Senior Sample | Sample mean | proportion | proportion*150,000 |
|---|---|---|---|
| Total Income | 119028.80 | | |
| Income from: | | | |
| Earnings | 56101.87 | 0.471 | 70699.5 |
| Social Security | 16542.07 | 0.139 | 20846.3 |
| Pensions | 17113.12 | 0.144 | 21565.9 |
| Unemployment Compensation | 33.78 | 0.000 | 42.6 |
| Dividends | 7757.75 | 0.065 | 9776.3 |
| Interest or Rent | 18653.95 | 0.157 | 23507.7 |
| Other | 2826.31 | 0.024 | 3561.7 |
| | | 1.000 | 150000.0 |
| Non-senior Sample | | | |
| Total Income | 190108.00 | | |
| Income from: | | | |
| Earnings | 175363.00 | 0.922 | 138365.8 |
| Social Security | 460.73 | 0.002 | 363.5 |
| pensions | 1146.54 | 0.006 | 904.7 |
| Unemployment Compensation | 97.60 | 0.001 | 77.0 |
| Dividends | 4232.91 | 0.022 | 3339.9 |
| Interest or Rent | 6784.32 | 0.036 | 5353.0 |
| Other | 2022.91 | 0.011 | 1596.1 |
| | | 1.000 | 150000.0 |

**Table A3.4 First-Stage F-Tests**

| Equation: | Tax Rate | Base M1 | Base M2 | Base M3 |
|---|---|---|---|---|
| First Stage F-test | 13.83 | 3.59 | 4.12 | 1.23 |
| P-value | 0.00 | 0.00 | 0.00 | 0.27 |

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