Income Inequality, Tax Policy, and Economic Growth*

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Abstract

We investigate how the reduction of income inequality through tax policy affects economic growth. Taxation at different points of the income distribution has heterogeneous impacts on households' incentives to work, invest, and consume. Using U.S. state-level data and micro-level household tax returns over the last three decades, we find that reducing income inequality between low and median income households improves economic growth. However, reducing income inequality through taxation between median and high-income households reduces economic growth. These asymmetric economic growth effects are attributable both to supply-side factors (i.e., changes in small business activity and labour supply) and to consumption demand.

JEL Codes: H2, H3, E2.

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Modern governments have utilised tax policy to not only raise capital for government operations but also to reduce income inequality among citizens. Progressive taxation with negative net tax rates for the lowest income households aims to achieve two distinct objectives: (i) to provide a minimum level of consumption for the low-income population, and (ii) to reduce income inequality between different groups of the population.[1] The underlying economic justification for this tax policy is that income inequality creates lower economic growth. Researchers find mixed evidence regarding the relationship between income inequality and economic growth.[2]

Our work makes three contributions. First, while there are various possible ways to reduce income inequality, our paper investigates how *tax policies that reduce income inequality* have affected economic growth in U.S. states in the last three decades. We find that the growth effect of redistribution through taxation is asymmetric depending on whether the reduction of inequality occurs in the below median part of income distribution or the above median part of income distribution. Our question is different from the literature that has investigated the impact of income inequality *levels* on economic outcomes, and separately, the literature on the impact of tax rates on economic outcomes. Second, we investigate both supply-side and demand-side mechanisms through which tax policies that reduce income inequality affect economic growth. We find taxation at different points of the income distribution has asymmetric impacts on households' incentives to supply labour, engage in small business activity, and consume. Third, our paper identifies the impact of tax policies that reduce income inequality from variation between relatively homogenous U.S. states. This compares to seminal work on economic growth that has (perhaps due to data unavailability in the past) focused on cross-country analysis, where heterogeneity across countries is arguably larger over many dimensions.[3]

[1]See Figure 1, which shows how income inequality is reduced in the U.S. through tax policy which effectively compresses the income distribution around the median household.

[2]Alesina and Rodrik (1994) and Perotti (1996) among others find that there is a negative correlation between average growth and inequality since the 1960s. Persson and Tabellini (1994) document that a similar negative relationship existed in nine developed economies since the 1830s. However, Forbes (2000) finds a positive relationship between income inequality and economic growth, and Barro (2000) finds a positive relationship between income inequality and growth in rich countries and a negative relationship in poor countries. See Bénabou (1996), Ostry *et al.* (2014), and Cingano (2014) for detailed surveys of the literature. Seminal work that uses data from U.S. states to study the impact of inequality on economic growth includes Partridge (1997) and Panizza (2002).

[3]Literature on endogenous growth of countries includes seminal work by Romer (1986), Lucas (1988), Barro (1990), and Barro (1991), among others. While we use eight major datasets for the project, the main dataset is a large sample of U.S. income tax returns, TAXSIM microdata, provided by the Internal Revenue Service (IRS) and made available to researchers by the National Bureau of Economic Research (NBER). Thus, our analysis is less prone to measurement error issues that can exist in cross-country data comparisons. Measurement error can cause estimation bias. For example, if a more unequal society underreports its inequality statistics and also grows slower, cross-country estimates of the impact of inequality on growth may suffer from a negative bias. Furthermore, compared to cross-country differences, economic development indicators and institutions are relatively more

We allow for asymmetric effects by distinguishing between the impact of tax policy on households below the median income level and on those above the median income level. We find that poverty alleviation, i.e. reduction of income inequality, between low-income and median-income households improves economic growth. The reduction of the income gap between the above median households and the median household, however, has a negative effect on GDP growth. As discussed later, these results are obtained using an instrumental variables approach with controls for marginal tax rates, state fixed effects, year fixed effects, and other important economic characteristics.

We explore three major components of economic growth as well. We find that reducing income inequality between below median and median households, in most instances, encourages female labour supply and small businesses growth, as well as consumption expenditure growth. However, reducing income inequality through taxation between above median-income households and median-income households reduces female labour supply, small business growth and job creation. As far as we know, this asymmetric effect of tax policy across the income distribution has not been shown empirically before this paper.

Our empirical strategy relies on within-state variation in tax policies that reduce income inequality to explain within-state variation in growth rates of U.S. states over time. We utilise a simple measure that calculates the changes in income distribution induced by income tax policy for each state using actual tax return data. Specifically, the measure calculates the additional average income tax paid for each additional dollar earned by a person at the higher/lower income level, compared to the reference point of the median income level household. Since this is analogous to a contraction function on income distribution, we refer to it as the contraction factor. As we show, this cross-sectional differential tax rate measure is able to explain economic growth even after controlling for the average marginal tax rate for each state over time. This is because an individual considers the impact of tax policy on her income in two dimensions. She considers the tax-induced change in her income with respect to the reference point of median income household. This is in addition to the impact of tax policy on her marginal dollar, where her reference point is herself. We calculate contraction factor between the median income and bottom income group, and the median income and top income group for each U.S. state and year from 1979 to 2008.

Our contraction factors are potentially endogenous to the GDP growth due to the concern that tax poli-

homogenous across U.S. states. This allows us to assume that the same underlying economic relationship between GDP growth, tax policy, and inequality exists across states, which is more defensible than a similar assumption regarding countries.

cies may respond to economic conditions. To address such concerns, we use two separate sets of exogenous instrumental variables (IV). We estimate our model using a generalised method of moments approach developed by Blundell and Bond (1998) (system GMM), which refines the approach of Arellano and Bond (1991) for panel data that is persistent. The first set of exogenous instrumental variables are the exogenous tax shocks identified by Romer and Romer (2009, 2010), later refined by Mertens and Ravn (2013) at the national level, and their interactions with state-specific initial income inequality and initial propensity towards charity. We also conduct our analysis based on an alternative set of exogenous instrumental variables that are political and demographic measures in each state.

Our results contribute to the literature on tax policy and economic growth. Theoretical predictions regarding the impact of taxes on economic growth are mixed.[4] Thus, the question is primarily an empirical one. The empirical literature has investigated the effects of taxation on economic growth within the U.S., across U.S. states, and across countries. Using U.S. post-WWII data, recent studies find that a positive change in taxes has a negative impact on GDP growth.[5] Helms (1985) and Reed (2008) focus on state-level taxes and economic growth. There are also a large number of studies using cross-country data, which generally find negative effects of tax increase on output.[6] Building upon this literature, we show that redistributive taxation has heterogeneous effects on economic growth.

The literature that studies the relationship between inequality and economic growth has provided mixed predictions.[7] On one hand, inequality may reduce economic growth. First, political economy theory suggests that greater inequality is conducive to the adoption of distortionary redistributive tools and growth-retarding policies, which hurt economic growth.[8] Second, in the presence of financial market imperfections,

[4]Mirrlees (1971), Okun (1975) and Becker (2011) argue that taxes reduce economic growth by dampening incentives to work and invest. Barro (1990) shows that taxes can be beneficial for economic growth in the presence of public goods, but as government size increases, the benefits are outweighed by the costs of taxation. Bénabou (2000) shows that taxation can help growth if it finances public investment. Saint-Paul and Verdier (1993, 1997) shows that higher health and education spending benefits the poor, helping to offset labour and capital market imperfections.

[5]Blanchard and Perotti (2002) finds positive tax shocks have negative effects on output in the U.S. from 1947 to 1997. Romer and Romer (2010) find that a tax increase of 1 per cent of GDP implies a 3 per cent fall in output in the U.S. economy from 1947 to 2007. Mertens and Ravn (2013) find that short-run output effects of tax shocks are large in post-WWII U.S. data. They also find that it is important to distinguish between different types of taxes when considering their impact on the labour market and on expenditure components. Barro and Redlick (2011) find a large and significantly negative impact of an increase in average marginal tax rates on U.S. annual economic growth over the time period 1950 to 2006.

[6]See Koester and Kormendi (1989), Easterly and Rebelo (1993), Mendoza *et al.* (1997), Miller and Russek (1997), Kneller *et al.* (1999), Lee and Gordon (2005), Alesina and Ardagna (2010), Gemmell *et al.* (2011), Arnold *et al.* (2011), Ferede and Dahlby (2012), Padovano and Galli (2001), among others.

[7]Voitchovsky (2005) shows that inequality at the top end of the distribution is positively associated with growth, while inequality lower down the distribution is negatively related to subsequent growth.

[8]See, for example, Alesina and Rodrik (1994), Persson and Tabellini (1994), and Benhabib and Rustichini (1996).

higher inequality exaggerates the adverse effects of credit constraints on human capital accumulation and small business growth, reducing growth.[9] Third, Murphy *et al.* (1989) show that an equal society with homogenous tastes helps to create a large market for domestic manufacturers. On the other hand, greater inequality might increase growth. Higher inequality provides the incentives to work harder, invest more and undertake risks to take advantage of high rates of return.[10] Higher inequality can also foster aggregate savings and therefore capital accumulation because the rich have a lower propensity to consume.[11] Our results show that tax policy that reduces income inequality can have asymmetric effects on economic growth.

Kuznets (1955) conjectured that inequality increases in the early stages of economic development for a country (due to industrialisation and urbanisation). As industries attract a larger fraction of the labour force, inequality starts decreasing. Aghion and Williamson (1998) note that up to the 1970s, the prediction of Kuznets (1955) was corroborated by data. However, in recent times, wage inequality between and within groups of workers has been increasing.[12] This evidence provides support for action by policy makers to reduce income inequality.[13] Our results demonstrate that reduction of income inequality between all income groups may not have similar effects. When income inequality is reduced between above median households and median households, economic growth may decrease. Our results do not suggest what the optimal tax rate at various levels should be.[14] We document the asymmetric nature of redistributive tax policies on economic growth and argue that policymakers should not assume that reducing income inequality would necessarily translate into economic growth, as the opposite occurs in some cases.

1 Taxes, Incentives and Contraction Factor

This section discusses relevant U.S. tax policy, our main variable of interest and the source of variation in our empirical analysis.

[9] See, for example, Galor and Zeira (1993) and Galor and Moav (2004).

[10] See, for example, Mirrlees (1971), Lazear and Rosen (1981), Rebelo (1991), Heckman *et al.* (1998) and Guvenen *et al.* (2013).

[11] See Kaldor (1956) and Bourguignon (1981). Forbes (2000) shows that an increase in a country's level of income inequality has a significant positive relationship with subsequent economic growth.

[12] See, for example, Katz and Murphy (1992), Juhn *et al.* (1993), and Piketty and Saez (2003).

[13] Blundell *et al.* (2008) show that such redistributive tax policies in the U.S. have helped reduce consumption inequality, even in the presence of income inequality.

[14] See Diamond and Saez (2011) for a survey of the literature on optimal taxation. Recent papers include Conesa *et al.* (2009), Piketty *et al.* (2014) and Holter *et al.* (2014) among others.

1.1 Progressive Taxation and Tax Credits

Income inequality reduction through tax policy is obtained through two main mechanisms: progressive taxation, which leads to higher marginal taxes for higher income households, and tax credits which provide negative tax rates for the lower income households. Our data on tax returns is the TAXSIM microdata from NBER, prepared by the Statistics of Income Division of the Internal Revenue Service (IRS) for public use. The tax data, discussed in Appendix B.1, help show that progressive taxation and tax credits "compress" the income distribution. To illustrate the "compression" effect, we compare the national before-tax income distribution and after-tax income distribution in Figure 1. The figure utilises the full sample of TAXSIM tax return data for all U.S. states for the years 1979 to 2008, in 2009 U.S. Dollars.[15] The mean pre-tax income (AGI) in 2009 U.S. Dollars is $\$49,548$, with inequality measured by the standard deviation of log income of 1.188. The darker region shows that the after-tax distribution is shifted to the left and contracted – it has a lower mean ($\$42,508$) and smaller standard deviation of log income (1.139). Measured in terms of reduction of variance of log income, the income inequality on average is reduced by about 8% through taxation.

The progressive taxation and tax-credit policies, in effect, are moving the after-tax income of both the lower and upper-income households towards the median to reduce inequality. Thus, the median income household is a natural reference point to measure the impact on inequality reduction through tax policy. In Section 1.2, we measure the extra tax liability for each additional dollar earned by the lower income and upper-income households compared to the reference household (the median income household) respectively.

1.2 Contraction Factor

In this section, we propose a simple measure that evaluates the changes in income inequality induced by the progressive tax policy. Let $Income_{s,t}(i)$ denote the average pre-tax income for households in the ith percentile in the income distribution of state s in year t, and $Tax_{s,t}(i)$ denote the associated total income tax liability in year t and state s. The before-tax income inequality is then measured by the difference between pre-tax income percentile i and j in a given year t, $Income_{s,t}(i) - Income_{s,t}(j)$. Similarly, the after-tax income inequality in year t and state s is given by $(Income_{s,t}(i) - Tax_{s,t}(i)) - (Income_{s,t}(j) - Tax_{s,t}(j))$.

[15] Throughout this paper, all monetary figures are deflated to 2009 USD using the GDP deflator from BEA.

Using the median income household as the reference point, we define the reduction in the after-tax income inequality as a fraction of the before-tax income inequality, referred to as the "contraction factor" $C_{s,t}(i)$, as follows:

$$
\begin{aligned}
C_{s,t}(i) &\equiv 1 - \frac{(Income_{s,t}(i) - Tax_{s,t}(i)) - (Income_{s,t}(50) - Tax_{s,t}(50))}{Income_{s,t}(i) - Income_{s,t}(50)} \\
&= \frac{Tax_{s,t}(i) - Tax_{s,t}(50)}{Income_{s,t}(i) - Income_{s,t}(50)}. \qquad (1)
\end{aligned}
$$

In a progressive tax system, $Tax_{s,t}(i) - Tax_{s,t}(50)$ and $Income_{s,t}(i) - Income_{s,t}(50)$ share the same sign. Further, as long as taxes are used to reduce income inequality, $C_{s,t} \in [0,1)$. We suppress the subscript s,t of $C_{s,t}(i)$ for simplicity. The contraction factor measures the taxation induced reduction in the income gap between the income percentile of interest and the median income households. The contraction factor can be interpreted as the additional average income tax paid for each additional dollar earned by a person at the ith income percentile, compared to the median income.[16]

Our main analysis will rely on two contraction factors: $C(90)$, that measures the effects of taxation on after-tax income gap reduction between 90th percentile household (high income household) and the median household; and $C(10)$ which evaluates the reduction of the after-tax income gap through taxation between the median household and the 10th percentile household (low income household). The top and bottom panels of Figure E1 in the Appendix graphically demonstrate an increase in contraction factors $C(90)$ and $C(10)$ respectively.[17]

1.3 Source of Variation

The source of variation in contraction factors comes from changes in state or federal tax schedules and changes in the underlying income distribution. Figure 2 shows the distribution of contraction factors in our analysis across states for the sample period. The figure suggests that there are variations in both contraction

[16]Our variable is different from the average marginal tax rate (Barro and Redlick, 2011) that affects an individual's decision to earn an additional dollar given her present income and income tax rate. Barro (1990) and Barro and Redlick (2011) among others, have discussed the importance of marginal tax rates for economic growth. In contrast, the contraction factor aims to capture the impact of tax policy-induced reduction in income inequality, with respect to the median household as the reference household, on economic growth. Our framework for analysis considers the impact of the contraction factors for above-median households and below-median households separately, and also controls for changes in average marginal tax rate over time.

[17]In our robustness check section (Section 5), we also show that our analysis yields similar results if we use different thresholds for above median and below median contraction factors such as $C(80)$ and $C(20)$.

factors between and within states. Figure 3 plots the standard deviations of contraction factors for each state showing that there is within-state variation.[18] Table D2 in the Appendix summarises the average one period lagged contraction factors as well as average per capita annual GDP per capita growth rates for the 49 states in our analysis for the sample period of 1980–2009. The figures and table suggest significant variation in contraction factors over time and across states.

Furthermore, as seen in the left panel of Figure 4, there is a lot of variation in average marginal tax rates across states and over time. Once we demean the average marginal tax rates for each state, the demeaned average marginal tax rates range between -0.05 and 0.07 and follow a bimodal distribution. The left panel of Figure 5 plots the average state income tax rates across all states and years. The right panel of Figure 5 shows the demeaned average state income tax rates distribution.

Lastly, the Earned Income Tax Credits (EITCs) also provide additional variation in the net tax liability across states and over time. The federal EITC, established in the tax code in 1975, is a refundable tax credit for low- and moderate-income working people, particularly those with children. The amount of EITC benefit depends on a recipient's income and number of children. Over time, many states have also established their own EITCs to supplement the federal credit. Figure 6 plots the number of states that have refundable state EITCs over time.[19] State EITCs are typically set as a percentage of the federal credit and these match ratios generally differ by states and change over time. Figure 7 plots the distribution of state refundable EITC match as a percentage of federal EITC over our sample period.[20]

2 Framework of Analysis

This section discusses our empirical specification and estimation strategy.

[18]Figure E2 in the Appendix plots the levels of contraction factors for each state averaged over the same time period.

[19]As of 2012, 26 states have enacted state EITCs: Colorado, Connecticut, Delaware, District of Columbia, Illinois, Indiana, Iowa, Kansas, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Nebraska, New Jersey, New Mexico, New York, North Carolina, Ohio, Oklahoma, Oregon, Rhode Island, Vermont, Virginia, and Wisconsin. Some of these state EITCs are refundable, and some are not. In addition, a few local EITCs have been enacted in San Francisco, New York City, and Montgomery County, Maryland.

[20]Table D3 in the Appendix reports correlation between the state-level Gini coefficient in a given year with the contraction factors $C(10)$ and $C(90)$ in the state in that year. A higher level of income inequality measured by Gini correlates with less contraction. We also note that the Gini coefficient correlates more strongly with the ratio of income of 90th and 50th percentile households than with the ratio of 50th and 10th percentile households. This is due to the positively skewed income distribution. This observation provides additional motivation for using contraction factors which allow for distinguishing between the impact of above and below median households on the economy.

2.1 Empirical Specification

We estimate the effects of below median and above median contraction factors on state-level annual per capita economic growth, using the following specification:

$$\begin{aligned}\log GDP_{s,t} - \log GDP_{s,t-1} =& \kappa_1 \cdot \log C_{s,t-1}(10) + \kappa_2 \cdot \log C_{s,t-1}(90) \\ &+ \gamma_1 \cdot (AMTR_{s,t-1} - AMTR_{s,t-2}) \\ &+ h_1 \cdot \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \cdot \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} \\ &+ \alpha \cdot \log GDP_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t} \qquad (2)\end{aligned}$$

where $GDP_{s,t}$ is the per capita real GDP for state s and year t, $C_{s,t-1}(90)$ is previous years' contraction factor between the 90th percentile household and the median household; we use it as a measure of income inequality reduction between high income households and median income households. $C_{s,t-1}(10)$ is previous year's contraction factor between the 10th income percentile household and the median household; it represents the income inequality reduction between median income households and low income households. Lagged contraction factors address the possible concern of contemporaneous effects.[21] $AMTR_{s,t-1}$ is the average marginal income tax rate, i.e. the additional tax paid on the next dollar earned, in state s and year $t-1$. $Income_{s,t-1}(10)$, $Income_{s,t-1}(50)$, and $Income_{s,t-1}(90)$ are income levels at 10th, 50th, and 90th, respectively. $X_{s,t-1}$ is a vector of additional controls, δ_s denotes state fixed effects, and η_t denotes time fixed effects.

The coefficient κ_1 measures the effect on year t's GDP growth rate from a one per cent increase in below median contraction factor $C(10)$, and the coefficient κ_2 measures the effect on year t's growth rate from one per cent increase in above median contraction factor $C(90)$. The contraction factors $C_{s,t-1}(10)$ and $C_{s,t-1}(90)$ depend on the predetermined income distribution of state s in year $t-1$ and on the income tax legislation (both federal-level and state-level). We are interested in both the sign and the magnitude of κ_1 and κ_2 to establish that tax policies that reduce income inequality have asymmetric effects. As noted, the contraction factors are based on the income distribution and tax legislation at year $t-1$, which are predetermined with

[21] For example, an unobserved shock $\varepsilon_{s,t}$ that affects the growth of economy at time t, could also affect households' choices and thus income, which ultimately affects the contemporaneous contraction factor C_t at time t.

respect to the GDP growth rate in year t. This alleviates simultaneity concerns. However, there is still an endogeneity concern regarding the contraction factors since they are driven by potential endogenous tax legislation changes. We address this endogeneity concern by using instrumental variables, which are discussed in detail in Section 2.2.

As discussed before, previous literature has also shown that changes in marginal tax rates have important implications on economic growth because they affect households' current choices on employment and consumption compared to the previous period.[22] As marginal tax rates increase, incentives to work decline for the same household irrespective of the tax rate of other households. Therefore, following Barro and Redlick (2011), we control for changes in average marginal tax rate between year $t-1$ and $t-2$ ($AMTR_{s,t-1} - AMTR_{s,t-2}$).[23] Furthermore, Forbes (2000) show that levels of income inequality affect economic growth. Hence, we include $\log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)}$ and $\log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)}$ to capture the level of income inequality between the 90th percentile income household and median household, and median household and 10th percentile household respectively.

Lastly, Mankiw *et al.* (1992) show that a neoclassical growth model (see Solow, 1956) augmented with accumulation of human capital as well as physical capital yields an empirical specification where GDP growth rate $\log GDP_{s,t} - \log GDP_{s,t-1}$ depends on level of GDP in the previous period (i.e. $\log GDP_{s,t-1}$) and accumulated human capital level. Within the framework of the neoclassical growth model, $(1+\alpha)$ in Equation 2 measures the rate of convergence in economic growth. We measure human capital level using average years of higher education in the working age population ($Education_{s,t-1}$). Finally, we control for the state government per capita real direct general expenditure divided by the per capita real GDP (*Government Expenditure*), because Barro and Redlick (2011) and Helms (1985) find that government expenditure affects GDP growth (see Table 1, Panel B for details).

[22]Literature includes, but is not limited to Mirrlees (1971), Barro (1990), Barro (1991), Alesina and Rodrik (1994) and Barro and Redlick (2011).

[23]Following Barro and Redlick (2011), when computing $AMTR_{s,t-1} - AMTR_{s,t-2}$, we calculate both $AMTR_{s,t-1}$ and $AMTR_{s,t-2}$ based on year $t-1$ income in state s to eliminate the channel whereby higher income shifts people into higher tax rate brackets for a given tax law.

2.2 *Estimation Strategy*

Our key parameters of interest are the coefficients of contraction factors, κ_1 and κ_2, in Equation 2. As already discussed in the previous section, a potential concern with OLS is that tax policy may be an endogenous response to the economic conditions. To address this potential endogeneity concern, we use two mutually exclusive sets of exogenous instrumental variables and estimate our model using a generalised method of moments approach developed by Blundell and Bond (1998). The reason we use two sets of instrumental variables is because despite our attempts at convincing the reader that either of these is an appropriate set of instruments, each set could still have its own concerns. Corroboration of the results with mutually exclusive instruments provides additional confidence.

2.2.1 *Main instruments*

We use the exogenous tax liability shocks narratively identified by Romer and Romer (2009, 2010) and later refined by Mertens and Ravn (2013) to form exogenous instruments for changes in our contraction factors and marginal tax rates (see the appendix in Mertens and Ravn (2013) for more details). Romer and Romer (2009) identified a series of tax liability changes that are exogenous to economic growth in the U.S. from 1945 to 2007. Using a narrative approach based on congressional reports and other government administrative data, Romer and Romer (2009) classify tax liability changes as exogenous if the motivation for the legislative action is either arising from inherited deficit or from ideological concerns.[24] Mertens and Ravn (2013) further extend the analysis by distinguishing between changes in personal and corporate income tax liability, and by distinguishing between unanticipated and anticipated tax changes on the basis of the implementation lag.

These tax shocks, identified by Romer and Romer (2009) and refined by Mertens and Ravn (2013), are exogenous to the current conditions of the economy in the state, because they relate to unanticipated tax liability changes that are not a response to the growth prospects of the economy in the state.[25] Figure E3

[24] Romer and Romer (2009) classify every significant tax bill into one of the four categories based on the underlying motivation for the tax change: responding to a current or planned change in government spending, offsetting other influences on economic activity, reducing an inherited budget deficit, and attempting to increase long-run growth. Romer and Romer (2009) classify the last two types of tax changes as exogenous to the current state of the economy in the sense that they are not a response to the growth prospects of the economy.

[25] Furthermore, in practice, these tax liabilities changes are often related to the changes in progressivity of the tax schedule and thus correlate with changes in contraction factors as well as marginal tax rates. In particular, Barro and Redlick (2011) use the

in the Appendix reports personal income tax shocks from Mertens and Ravn (2013) and reports average contraction factors for each year from 1979 to 2007.[26] During this time period, the largest exogenous change in personal income taxes relates to the Jobs and Growth Tax Relief Reconciliation Act of 2003, which includes across-the-board reductions in marginal tax rates as well as increases in child credit. The largest exogenous increase in personal income taxes relates to Omnibus Budget Reconciliation Act of 1993, which increased income taxes, mostly for high earners.

The impact of the exogenous tax shocks at the national level varies based on conditions present at the state-level. We focus on two initial conditions which are relevant to contraction factors: initial state-level inequality measures (as measured by 90th/50th percentile and 50th/10th percentile log income ratio in 1979), and initial attitude towards charity (measured by the share of charity to income ratio in 1979).[27] In the presence of state and year fixed effects, these tax shocks and their interactions with state-specific initial conditions satisfy the exclusion restriction because the within-state variations of these variables come from unanticipated tax liability changes, and are exogenous to the growth prospects of the state's economy. Furthermore, these tax shocks have a high positive correlation with shifts in marginal income tax rates; and the interactions of these tax shocks with state-specific initial conditions strongly correlate with contraction factors (relevance condition). Other researchers, such as Barro and Redlick (2011), have also used these tax shocks as instruments for changes in the marginal tax rate in the GDP growth regression analysis. A detailed discussion regarding the relevance of these exogenous instruments to our contraction factors is in subsection 4.1 of Section 4 where we discuss empirical results. Table D5 in the Appendix reports the results.

Potential Concerns Regarding Main Instruments: A concern with this set of instruments may be that of reverse causality: actual or expected shocks to GDP might induce changes in tax policies and revenues. To this end, we rely on the work by Romer and Romer (2009) and Mertens and Ravn (2013) which carefully identify and argue that the tax shocks used in this paper are not an endogenous response to current economic conditions or expected economic growth perspectives. We also would like to point out that all our

changes in exogenous tax liabilities identified by Romer and Romer (2009) to form an instrument for changes in the marginal tax rate in the GDP growth regression analysis.

[26] In particular, Mertens and Ravn (2013) create the personal income tax shock as the narratively identified exogenous personal income liability change divided by previous personal taxable income, z_{pi}; the corporate income tax shock is defined as narratively identified exogenous corporate income tax liability changes scaled by previous period corporate profits, z_{ci}. Mertens and Ravn (2013) provide both quarterly and annual data; we choose the annual level data for our analysis.

[27] To develop a measure of attitude towards redistribution, we collect total charitable contributions, cash and assets, as recorded in tax returns from the TAXSIM data. We scale the total charitable contributions by the total income in the state.

specifications utilise lagged controls, and thus the tax changes are of the previous period.

Another concern may be that of simultaneity (skill or task biased technical change might induce relevant changes in tax revenues and affect the growth rate). Since such changes are at the aggregate level, the inclusion of year fixed effects will capture these effects. To the extent state economic conditions are persistent, we include lagged real GDP per capita as a control, along with state fixed effect for time-invariant state specific conditions. Further, state-specific inequality levels and education are also included as controls in our specification. However, one may still have concerns regarding whether our main instruments are appropriate. The next section introduces an alternative set of instruments that depends on a different identification strategy. In all of our estimation results, we compare the results from both these two sets of mutually exclusive instruments, in order to alleviate the potential concerns regarding each set of individual instruments.

2.2.2 Alternative instruments

Our alternative set of instruments utilises political and demographic measures in each state. For political measures, we use election results for sitting legislators in the state house and senate, and for state governor.[28] The election data contains the length of term for each elected official, so we are able to construct a time series database of the party in each legislative and gubernatorial seat for each year.[29] We then create three political climate variables that measure the strength of the Democratic Party in the legislative and executive branches of each state's government. The first is an indicator variable that indicates whether there is a Democratic governor ($\text{Governor}_{s,t}$). Our other two instruments measure the strength of the Democratic party's legislative control using the share of legislative seats occupied by Democrats in the state senate, i.e. upper house ($\text{State Senate}_{s,t}$) and the state house ($\text{State House}_{s,t}$). Panel B of Table 2 summarises our political instruments.

We also use three demographic measures that can affect state policies on tax credit as instrumental variables: the fraction of population aged 65 and older ($\text{Elderly}_{s,t}$), the fraction of population aged 5 to 17 ($\text{Age 5 to 17 population}_{s,t}$), and the fraction of households headed by single mothers ($\text{Single Mother}_{s,t}$) (two

[28] We use the State Legislative Election Returns (Klarner *et al.*, 2013) database, and the Congressional Quarterly Press Voting and Elections Collection data on gubernatorial elections (CQ Press, 2014). See Appendix B for more details.

[29] Nebraska's state legislature is unicameral and does not specify party affiliations for candidates during elections. As a result, the Nebraska state legislative data is missing.

of the demographic instruments, fraction of old and young persons in population, were previously suggested by Helms, 1985). We consider a household to be a single mother household if the head of the household is an unmarried female with at least one dependent child under the age of 18.[30] Panel B of Table 2 summarises our demographic instruments for each state.

Potential Concerns Regarding Alternative Instruments: A concern with this alternative set of instruments may be that the election of political parties are endogenous to the economic conditions, or that political parties may affect other state-level policies which in turn affect the economy. Note that state-level economic controls include variables for state-specific economic conditions (income inequality, education), spending differences by political parties (government expenditure), marginal tax rate, persistence in output (last period's real GDP per capita) along with controls for state-specific heterogeneity (state fixed effects) and aggregate effects (year fixed effects). However, it is possible that political parties affect the economy beyond expenditure and taxes in a time-variant manner which is not very persistent. The two mutually exclusive set of instruments provide confidence that the instruments are not driving our results.

2.2.3 System GMM approach

In addition to the endogeneity of tax policy to state-level economic growth, one may be concerned about the possibility of Nickell bias in Equation 2 given a small $T = 29$ years and large $N = 49$ states.[31] Hence, we implement our estimation using the system GMM method developed by Blundell and Bond (1998). The system GMM approach is an improvement upon the difference GMM proposed by Arellano and Bond (1991). Such IV GMM methods have become increasingly popular in the empirical literature on inequality and economic growth (See, for example Forbes, 2000; Ostry *et al.*, 2014; Cingano, 2014).

Besides exogenous instrument variables, system GMM also utilises lagged values of control variables as internal instrumental variables in the estimation. Specifically, for our internal instruments, we use two period lagged log GDP per capita and one period lagged predetermined control variables.[32] Our estimation results are robust to using more lags as internal instruments. In our estimation table, we also report the

[30] See Appendix B for more details.

[31] Nickell (1981) provided analytical expressions for the bias in estimates in dynamic models with individual fixed effects when the time period is short and the number of individuals is large.

[32] As shown in our specification, the controls for our primary estimation are lagged one period: inequality levels relating the 50th and 10th percentile incomes and 90th and 50th percentile incomes, average years of higher education, state government expenditure.

Arellano-Bond test for autocorrelation, as well as the test for over-identification and validity of instrument variables, all of which provide confidence in our results.

3 Data

We utilise eight major data sources to construct our state-year level panel dataset. Data include information on GDP growth, income distribution, taxes, and other economic control variables. The state-level GDP per capita growth rate is constructed from the U.S. Department of Commerce Bureau of Economic Analysis (BEA). We use TAXSIM data to obtain information on contraction factors, income percentiles, and the corresponding tax liability and average marginal tax rates in each state and each year. We also utilise the TAXSIM data to gather data on initial income inequality and charitable contributions in 1979 to create our instruments related to attitudes towards inequality and redistribution.

Additional datasets include (i) U.S. Census Bureau for state government finances, (ii) Mertens and Ravn (2013) for narratively identified personal and corporate income tax shocks exogenous to economic growth, (iii) Congressional Quarterly Press and (iv) State Legislative Election Returns (SLER) for election results, (v) Current Population Survey (CPS) data for state-level schooling and labour market variables, (vi) the Business Dynamics Statistics (BDS) database for information on small businesses, and (vii) the BEA for personal consumption expenditures by state and state income growth. Table 1 Panel A, summarises all the dependent variables in our analysis and their data sources. Panel B of Table 1 lists our explanatory variables and their sources. The exogenous instruments have already been discussed in Section 2 along with the estimation strategy, appendix Section B discusses dependent and explanatory variables.

Table 2 provides summary statistics for all of the variables used in this paper. All statistics shown are pooled across all states and years from 1980 to 2009 for dependent variables and 1979 to 2008 for independent variables, as we measure the effect of our lagged regressors on our variables of interest. All the nominal figures are deflated to 2009 dollars using GDP deflator. Panel A reports summary statistics for all the dependent variables in our analysis. The equal weighted average real GDP per capita growth from 1980 to 2009 in U.S. states is 1.46% with a median growth rate of 1.67%. The equal weighted pooled standard deviation of growth rate is significant at 2.8%. Regarding small business activity variables, the number of establishments of size 20 to 49 grows at a 1.84% rate. The net job creation rate by continuing establishments is 0.8%. Our calculations on labour supply show that on average 79.3% of the working age male population are employed, while 65.7% of working age females are employed. On average, male employment decreases by 0.3 pp per year, while female employment increases by 0.3 pp per year. Lastly, BEA data shows that the average real total personal consumption expenditure (PCE) per capita is $30,217 in 2009 U.S. Dollars, and has an annual growth rate of 1.5% from 1998 to 2009. The average real PCE per capita on durable goods is $3,871 and the annual growth rate is −0.31%. On average, real PCE on nondurable goods and services per capita is $26,346 in 2009 U.S. Dollars, and the average annual growth rate is 1.7%.

Panel B reports summary statistics pooled across all states and years from 1979 to 2008 for explanatory variables, controls, and instruments as these variables enter our estimation as lagged measures. The contraction factor between the median and 10th percentile household is 9%, and that between the 90th and median household is almost double of that at 17%. Thus, the marginal tax rate almost doubles on the additional income between the two groups. The other key explanatory variable we utilise is the annual change in the average marginal tax rate, which has an average increase of 0.53 pp, and ranges from a minimum of −4.6 pp to a maximum of 6.9 pp across states.

We also include several controls identified in the literature as possible determinants of GDP growth rate. This is in addition to state and time fixed effects, which are included in our instrumental variables specification. We control for the level of inequality in each state by considering income ratios between different percentiles. On average, the 90th percentile income is 3.2 times the median income, and the median income is on average 5.9 times the 10th percentile income. Higher education provides a measure of human capital, and the average years of schooling beyond the 12th grade is 1.4 years. We note that states on average spend $2,384 per capita on direct general expenditures, which includes all state spending that is not classified as intergovernmental, utility, liquor stores, and employee-retirement or other insurance trusts, while the average state spending as a portion of GDP is approximately 6.25%. Lastly, we can see that state personal income per capita grows at an average rate of 2.1%.

Our system GMM analysis with the main set of instruments employs exogenous tax shocks to personal and corporate income as identified by Mertens and Ravn (2013), as well as interaction terms with inequality levels and charitable contributions in 1979. The average personal income tax liability shock is -0.06% of the previous period personal taxable income, with a minimum of −1.1% and a maximum of 0.44%. The average corporate income tax liability shock is -0.04% of the previous period corporate profits, with a minimum of -3.28% and a maximum of 7.38%. We interact tax shocks with the inequality levels of 1979, where the 90th percentile income was 2.7 times the median income, and the median income was 5.5 times the 10th percentile income. Furthermore, we interact these tax shocks with the charitable donations in 1979, which were on average 1.54% of income.

We also use political and demographic measures as an alternate set of instruments within our system GMM analysis. Regarding political climate, Democrats hold on average 57% of the seats in the state senate and also hold 57% of the seats in the state house. Democrats hold governorships in 53% of the observations. Demographically, we note that 12.3% of the population is older than 65 years of age, while 19.1% of the population is between ages 5 and 17. Lastly, 6.6% of the households are headed by a single mother.

4 Empirical Results

This section first conducts an estimation of the relationship between the reduction of income inequality through tax policy and economic growth. For this, we use system GMM with two sets of mutually exclusive instrumental variables to gain confidence in our results. Then, we explore three important channels through which reducing income inequality through tax policy affects economic growth: (i) Employment, (ii) Business activity, and (iii) Consumption. Finally, we explore the sources of asymmetric effects of the contraction factors on economic activity.

4.1 Income Inequality, Tax Policy and Economic Growth

Table 3 reports the results of the impact of the contraction factor on economic growth. Column (1) does not include any controls other than the below median contraction factor, and Column (2) adds the above median contraction factor. The raw correlations suggest that these two contraction factors have asymmetric effects. We do not discuss additional OLS results because an important concern is that an unobservable or omitted variable which is correlated with the contraction factor and GDP growth rate may drive OLS correlations. Specifically, an important issue maybe that tax policy driving the contraction factors could be itself endogenously chosen by policymakers in response to economic conditions that also affect GDP growth rate in the state.

Hence, our main specification in Column (3) utilises an IV approach with system GMM with an exhaustive set of controls. In Section 2, we have already discussed the estimation strategy and the instruments. The coefficients on the contraction factors in Column (3) of Table 3 show that contraction factors have a significant impact on per capita economic growth.

The IV estimates in Column (3) show that a one per cent increase in the contraction factor between the 10th percentile household and the median household increases the GDP per capita growth rate by 0.11 pp. At the same time, a one per cent increase in the contraction factor between the 90th percentile household and the median household, by increasing taxes by one per cent on the 90th percentile household reduces GDP growth rate by 0.24 pp. Column (4) reports the results for our alternative set of instruments and finds similar qualitative and quantitative results. Column (4) shows that one per cent increase in $C(10)$ increases economic growth by 0.083 pp. Regarding reduction of inequality between above median households and median households through taxation, Column (4) shows that one per cent increase in $C(90)$ reduces economic growth by 0.22 pp.

In all tables including Table 3, we conduct two important diagnostic tests for the System GMM estimator. First, to test for over-identifying restrictions, we report the Hansen J statistic and the corresponding p-value. The p-value fails to reject the null (the p-value is 0.675 in Column (3) for the main set of instruments), providing confidence in our choice of instruments. To address the instrument proliferation concern (Roodman, 2009a,b), we collapse the instrument matrix and the new tables make sure that the number of instruments is always less than the number of states, which is 49. Another important diagnostic is the test for autocorrelation of the residuals. If there is serial correlation in the first-differenced residuals at an order higher than one, then the moment conditions used by system GMM are not valid.[33] The results of the test are reported as M2 where 2 represents the second lag. The p-values of M2 are always above 0.10, suggesting that we cannot reject the null hypothesis of zero autocorrelation at the second-order. This provides us confidence that internal instruments provide valid moment conditions.

We run the first stage first difference regression and level regression that mimic those implied by the System GMM procedure (Bazzi and Clemens, 2013). We report test statistics for these first stage regressions for our main set of instruments and the alternative set of instruments in the Appendix in Tables D5 and D6,

[33] See Arellano and Bond (1991), Blundell and Bond (1998), and http://www.stata.com/manuals13/xtxtabond.pdf for discussions.

respectively. The first stage R^2 ranges between 0.15 to 0.33 for difference regressions and ranges between 0.69 to 0.71 for level regressions for the main set of instruments. The R^2 for the second set of instruments is similar. In all the first stage regressions, the overall F-stat p-value is < 0.001.

To directly test potential weak identification concerns, we report the Angrist-Pischke test statistics by mimicking two-stage IV regressions for difference regressions and level regressions as implied by System GMM, though separately. The first-stage first difference regressions using tax shocks as external instruments satisfy the weak identification test (Angrist-Pischke F test p-value < 0.001 for difference regression). The level regressions also satisfy the weak identification test (Angrist-Pischke F test p-values of < 0.05 for $C(10)$ level regression and < 0.01 for $C(90)$ level regression). By noting the Angrist-Pischke χ^2 p-values, we can also conclude that the difference and level equations reject the null that the equations are under-identified. For the second set of instruments (political and demographic instruments), we note that the level equations pass under-identification and weak identification tests at p-values of < 0.05.

The F-statistic shown in Table D5 for external instruments only shows that the first set of external IV, i.e. tax shocks, have additional identification power for difference equations in the system GMM (p-value < 0.001). Furthermore, as seen in the columns of Table D5, the coefficients in front of tax shock variables are statistically significant after controlling for other control variables and internal instruments. Similarly, the F-statistic shown in Table D6 for external instruments only shows that the second set of external IV, i.e. political and demographic instruments, have additional identification power for level equations in the system GMM (p-value < 0.001). This evidence suggests that these tax shock instruments have additional identification power. Additional discussion regarding the first stage is in Section C of the Appendix.

4.2 Components of GDP

Next, we focus on three main components through which reduction of income inequality through tax policy affect economic growth: (i) Labour supply, (ii) Activities of small businesses, and (iii) Consumption. Section 4.3 discusses the sources of asymmetry in the results regarding the impact of above and below median contraction factors on economic activity.

4.2.1 Labour supply

Table 4 reports the impact of above and below median contraction factors on our first component: labour supply. Columns (1) and (2) investigate the impact of contraction factors on the labour supply of males, and Columns (3) and (4) investigate labour supply of females using the two sets of instruments respectively. All columns show the most exhaustive IV GMM specification with year and state fixed effects. The columns look at the change in the annual employment rate among the working-age population in a state (See Panel A of Table 1 and appendix Section B for more details regarding variable construction). The reason that we consider males and females separately is due to recent work that shows taxes have a heterogeneous effect on labour supply based on gender as labour supply decisions are made at the household level.[34]

Column (1) shows that male labour supply does not seem to respond to contraction factors. Column (2), with an alternative set of instruments, corroborates these findings. However, Columns (3) and (4) show that female labour supply is statistically and economically significantly dependent on contraction factors. Column (3), where we conduct an instrumental variables approach with system GMM estimator as in Section 4.1 using our main set of instruments, shows that a one percent increase in the contraction factor between 10th percentile household and median income household achieved through taxes increases female labour supply by 0.10 pp. If the male of the household is already working, then it is intuitive that the effects should be observed on the dimension of female labour supply. The column also shows that reducing above median income inequality by increasing $C(90)$ by one per cent reduces female labour supply by 0.19 pp. Section 4.3 explores the asymmetry in the results for all three components of GDP together. Column (4), with an alternative set of instruments, reports similar qualitative results. Labour supply of females increases with $C(10)$, although the results are not statistically significant, and falls with higher $C(90)$. The results regarding the impact of above median contraction factor are statistically significant and the magnitude is similar to those in Column (3) which are results with our main set of instruments.

[34] Seminal work on household labour supply decisions include Chiappori (1988) and Blundell and Macurdy (1999). Recent work on taxes and decisions regarding labour supply include, but are not limited to, Kaygusuz (2010); Chakraborty *et al.* (2015).

4.2.2 *Small business activity*

Table 5 reports the impact of above and below median contraction factors on our second mechanism – small business growth and job creation in continuing small business establishments. We discuss characteristics of small businesses and reasons why we expect personal income tax rates to have an impact on small businesses later in the section.

We note that in Column (1), regarding the growth rate in the number of small business establishments, a one percent increase in below median contraction factor leads to 0.07 pp more small business establishments. At the same time, a one percent increase in the above median contraction factor reduces small business growth by 0.23 pp. Column (2) reports similar results, however this time, the positive impact of the below median contraction factor is not significant. When we consider job creation rates in Columns (3) and (4), we note that while both columns report numbers with similar signs, only Column (4) with the alternative set of instruments is statistically significant. Column (4) reports that a one per cent increase in the contraction factor between below-median households and median households through taxation leads to 0.095 per cent increase in job creation. The impact of taxation to reduce income inequality between above median households and median households is negative and significant: a one percent increase in $C(90)$ causes 0.13 pp lower job creation.

To understand our findings on small business growth and job creation, we need to consider both the demand and incentive effects of the redistributive effects of tax policy. Demand effects due to lower income households having a high marginal propensity to consume may lead to an increase in aggregate demand which may fuel some business growth. At the same time, entrepreneurs and small business owners face incentive effects from $C(10)$ and $C(90)$ since in many instances they face personal income tax rates.[35] A

[35] The distribution of small business income in the U.S. largely overlaps with the distribution of household income in general. Approximately 22 million businesses (that include unincorporated businesses, S-corporations and partnerships) face personal income taxes. Median income of small businesses is approximately $71,583 with 10th and 90th percentile at approximately $30,000 and $180,000 respectively. These numbers are quite similar to the income of households in the U.S. which are employed and in similar percentile position of the distribution. See http://www.payscale.com/research/US/Job=Small_Business_Owner/Salary for additional information obtained through a private survey regarding the distribution of income of small business owners in U.S. in recent years. This suggests that personal income taxes also affect small businesses that file as S-corporations and partnerships, both of which are pass-through entities regarding taxation, i.e. the income is passed through these entities and taxed as ordinary income of the owner in question. Data show that there are approximately 4.2 million S-corporations in the U.S. in 2011 and 3.3 million partnerships. Through the Technical Amendments Act of 1958, small businesses were allowed to file as Subchapter S corporations. The benefit of such a tax structure is that firms can operate as limited liability corporations, without suffering double taxation on business earnings. See http://taxfoundation.org/article/america-s-shrinking-corporate-sector for additional information regarding trends in the number of corporations in the U.S. In addition, please note that comparing the above number of incorporated firms with Census data on total number of establishments suggests that many businesses do not even

higher above median contraction factor $C(90)$ discourages relatively more profitable businesses to grow for the same reason as in the case of labour supply: running a business requires significant effort on the part of entrepreneurs and they may choose to remain employed elsewhere if the after-tax profits in relation to cost of effort are smaller.

Credit constraints among the low-income households may also bind strongly, leading to less entrepreneurship. Census data show that many of these businesses are quite small in terms of sales and thus presumably require little capital.[36] Data show that there are in total 23.8 million establishments in 2014, with 65% establishments have revenue (not income) of less than $25,000 per year. Hence, many such businesses could start without a large amount of capital. Thus, while small businesses started by lower income households may be credit constrained, which is potentially depressing the incentive effects through tax policy, we still find some positive effect of $C(10)$ on small business starts.

4.2.3 Consumption

Table 6 reports the impact of above and below median contraction factors on our final mechanism: personal consumption growth rates in states. The first two columns consider the impact of inequality reduction through tax policy on total personal consumption using the two sets of instruments. The next two columns focus on durable goods, and the final two columns focus on personal consumption growth rates of non-durable goods and services. It is important to note that the consumption growth rate data series is shorter, with data available only from 1998 to 2008.

The system GMM IV estimates in Column (1) show a significant positive relationship between the above median contraction factor and consumption growth. We see that decreasing inequality between 10th percentile and median household by increasing $C(10)$ one per cent results in the consumption growth rate increasing by 0.039 pp. We do not find that consumption growth is decreased statistically by reducing inequality between above median households and median households. This may be because budget constraints bind more often on households below median income, and the marginal propensity to consume is higher among low income households. Column (2), using an alternative set of demographic and political instruments, corroborates the findings of Column (1). Columns (3) and (4) focus on durable goods, and

incorporate (approximate 14.7 million).

[36]See http://censtats.census.gov/cgi-bin/nonemployer/nonsect.pl for census data.

find similar sensitivity to changes in contraction factor compared to overall consumption discussed earlier. However, these results are not statistically significant. Columns (5) highlights that the consumption growth rate of non-durable goods and services increases by 0.039 pp for each per cent increase in contraction factor for below median income households. Again, we do not see a statistically significant impact of reducing above median inequality.

In sum, this section shows that inequality reduction through tax policy for below-median households encourages female labour supply, small business activity and consumption, and ultimately economic growth. At the same time, inequality reduction between above median and median households through tax policy deters female labour supply and small business activity, hampering economic growth. Additional mechanisms may also be at work, but in this section, we only focused on labour supply, business activity and personal consumption.

4.3 Source of Asymmetry in Results

The three components of economic growth considered in this paper are driven by disparate mechanisms: incentive effects and demand effects. First, regarding the labour supply component, the obtained results may be driven by incentives to supply labor. This is because, as Table 4 shows, the male employment rate does not respond to changes in contraction factors. Female labor supply, which is more elastic empirically, responds significantly to contraction factors. Since a higher $C(10)$ encourages while a higher $C(90)$ discourages labor, they produce asymmetric effects.

Similar incentive effects are at play in the business creation component because entrepreneurs may also respond to $C(10)$ and $C(90)$. In addition, demand effects may also influence business creation in equilibrium. This is because a higher $C(10)$ leads to additional consumption by lower income households which have a higher marginal propensity to consume (MPC). Finally, $C(10)$ has a direct and positive effect on consumption growth which is our third component. This is because the transfer from low-MPC households to high-MPC households leads to higher aggregate consumption.

5 Robustness

Our results are robust to many alternative specifications. We report our main results (as shown in Table 3) with two alternative specifications next. The first set of alternative specifications utilise contraction factors calculated for the 15th and 85th percentile households (i.e. $C(15)$ and $C(85)$) in place of $C(10)$ and $C(90)$. Similarly, the second set of specifications reports results with contraction factors $C(20)$ and $C(80)$. These alternative specifications help address possible concerns that our results are extremely sensitive to the chosen points on the income distribution.

Table 7 reports the consolidated results from these robustness checks. Columns (1) and (2) report the first robustness check, while Columns (3) and (4) report the second test. All columns report IV results with system GMM estimator under the most exhaustive specification. The reported findings are similar to those reported in the main results. However, the coefficient of the below median contraction factor loses significance in Column (1). In general, we find that the results regarding below median contraction factor are somewhat less robust in terms of statistical significance. However, these results continue to underscore the asymmetric impact of the two factors on economic growth.

To further test the robustness of our results, we control for state-level unemployment rate in Columns (1) and (2) of Table 8. We find similar results as before. Columns (3) and (4) utilise the state-level market income distribution to calculate contraction factors. Market income is our original income measure (AGI), less the taxable portions of social security and unemployment insurance. We find, in Column (3), that a one per cent increase in above median income contraction factor results in a 0.141 pp decrease in economic growth, while a similar reduction in below median income contraction factor results in positive economic growth. Obtaining similar results using different income distributions gives us further confidence in our main findings. Column (4) provides similar results, and both factors have statistically significant coefficient in this case as well.

Table 9 checks for robustness of our results with additional controls. While we include the lagged level of GDP in our main specification, Column (1) and (2) include the lagged income growth rate as well. The results remain economically and statistically similar to those in our main specification. Columns (3) and (4) investigate whether controlling for welfare expenditure changes our main findings, especially in the case of the alternative set of instruments that includes demographic instruments. The motivation is Helms (1985), for example, who finds that state expenditure on public services and investment (such as highways and education) is good for economic growth and state expenditure on public welfare is bad for economic growth. Column (3) and (4) report similar results as our main specification suggesting that our results are robust to this test.

Table 10 utilizes alternative measures of reduction of income inequality through tax policy. For Columns (1) and (2), we use the national income distribution to calculate contraction factors, rather than the state income distributions. This ensures that income of the percentiles are constant across states, but also means that we are not comparing the same percentiles across states. The results remain similar. For Columns (3) and (4), we use an alternative inequality reduction measure that is the difference between before and after tax income inequality: Inequality Reduction(i) $= \left(\log \frac{\text{Income}(50)}{\text{Income}(i)} - \log \frac{\text{Income}(50)-\text{Tax}(50)}{\text{Income}(i)-\text{Tax}(i)}\right) / \left(\log \frac{\text{Income}(50)}{\text{Income}(i)}\right)$, where income i corresponds to 10th or 90th percentile for the below and above median households, respectively. Again, we find that the asymmetry of impact of inequality reduction for above and below median household on economic growth persists. The negative results for inequality reduction for above median households remains statistically significant.

6 Conclusion

Modern democracies have accepted the role of income taxation in addressing income inequality. This paper distinguishes the economic growth effect of income taxation in reducing inequality between below median and median income households, from the economic growth effect of taxation in reducing inequality between median households and above median households.

We find that taxation at different points of the income distribution has asymmetric impacts on households' incentives to invest, work, and consume. Tax policy that alleviates poverty improves economic growth in most instances. At the same time, we find that the reduction of incentives that is caused by a lower after-tax income gap between median and rich households reduces economic growth. This paper does not address optimal taxation and general equilibrium effects of tax policy. We also do not investigate the impact of specific tax policies and welfare programmes on economic growth.

Hopefully, our findings will help policymakers make more informed decisions regarding tax policy by carefully balancing social insurance with incentive preservation.

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Table 1: Variables List

Panel A provides descriptions and sources of the dependent variables in our ordinary least squares and instrumental variables approaches. Panel B provides descriptions and sources of all of the independent variables and instruments.

Panel A: Dependent Variables

Variable	Description	Source
Economic Growth		
$\Delta \log$ GDP	Changes in log real GDP per capita	BEA
Labor Supply		
ΔE_M	Changes in male employment rate (18-64 year olds, employed in previous week during March CPS)	CPS
ΔE_F	Changes in female employment rate (18-64 year olds, employed in previous week during March CPS)	CPS
Small Business Activity		
$\Delta \log$ Estabs	Changes in log of number of establishments (size 20 to 49)	BDS
Job Creation	Net jobs created as a fraction of total employment (2 year moving average) amongst continuing establishments (size 20 to 49)	BDS
Consumption*		
$\Delta \log \text{PCE}$	Changes in log of total personal consumption expenditures per capita	BEA
$\Delta \log \text{PCE}_{DG}$	Changes in log of durable goods personal consumption expenditures per capita	BEA
$\Delta \log \text{PCE}_{NDGS}$	Changes in log of nondurable goods and services personal consumption expenditures per capita	BEA

All the variables are at the state-level with annual frequency. All changes in monetary figures are deflated to 2009 US Dollars using GDP deflator.

*Consumption change variables are available from 1998 to 2008.

Panel B: Independent and Instrumental Variables		
Independent Variables		
$C(i)$	Contraction factor, i.e. reduction of income inequality, between ith percentile household and median household	NBER Taxsim
$\log C(i)$	Log of the contraction factor	NBER Taxsim
Δ AMTR	Changes in average marginal tax rate	NBER Taxsim
log GDP	Log real GDP per capita	BEA
$\frac{\text{Income}(i)}{\text{Income}(j)}$	Income ratio of the ith percentile to the jth percentile, where $i > j$	NBER Taxsim
$\log \frac{\text{Income}(i)}{\text{Income}(j)}$	Log of the income ratio of the ith percentile to the jth percentile, where $i > j$	NBER Taxsim
Education	Average years of schooling beyond grade 12 for population of age 25 to 64	CPS
Government Expenditure*	Log of state government direct general expenditure as a fraction of state GDP	US Census State Finances, BEA
Income Growth	Changes in log average state personal income	BEA
Tax Shock Instruments (Z)		
z_{pi}	Narratively identified personal income tax shock	Mertens and Ravn (2013)
z_{ci}	Narratively identified corporate income tax shock	Mertens and Ravn (2013)
$z_{pi} \times \log \frac{\text{Income}_{1979}(i)}{\text{Income}_{1979}(j)}$	Narratively identified personal income tax shock interacted with state inequality ratio in 1979	NBER Taxsim, Mertens and Ravn (2013)
$z_{ci} \times \log \frac{\text{Income}_{1979}(i)}{\text{Income}_{1979}(j)}$	Narratively identified corporate income tax shock interacted with state inequality ratio in 1979	NBER Taxsim, Mertens and Ravn (2013)
$z_{pi} \times \text{Charity}_{1979}$	Narratively identified personal income tax shock interacted with state share of total income contributed to charity in 1979	NBER Taxsim, Mertens and Ravn (2013)
$z_{ci} \times \text{Charity}_{1979}$	Narratively identified corporate income tax shock interacted with state share of total income contributed to charity in 1979	NBER Taxsim, Mertens and Ravn (2013)
Political and Demographic Instruments (Z')		
State Senate	Democratic share of seats in upper house	SLER**
State House	Democratic share of seats in lower house	SLER**
Governor	Dummy for Democratic governor	CQ Press
Elderly	Fraction of population aged 65 and older	CPS
Age 5 to 17 population	Fraction of population aged 5 to 17	CPS
Single Mother	Fraction of state households that are single mother households	CPS
Fixed Effects		
δ_s	State fixed effects	
η_t	Time fixed effects	

All changes in monetary figures deflated to 2009 US Dollars using GDP deflator.

* State government direct general expenditure includes state government expenditures for education services, social services and income maintenance, transportation, public safety, environment and housing, governmental administration, interest on general debt, and other general expenditures. It excludes all spending classified as intergovernmental, utility, liquor stores, and employee-retirement or other insurance trusts. Government Expenditure $= \log \frac{\text{Total Amount of Government Direct General Expenditure}}{\text{GDP}}$

** See Klarner *et al.* (2013)

Table 2: Summary Statistics

Panel A shows summary statistics (number of observations, mean, standard deviation, minimum, maximum, and median) for all the dependent variables that enter our specification, as well as the corresponding levels of each growth and change variable. Panel B shows the summary statistics for the main explanatory variables, controls, and instruments that enter our model, and the corresponding levels of each growth and change variable. All characteristics are at the state-level, and summary statistics shown are pooled across states from 1980 to 2009 for dependent variables and 1979 to 2008 for independent variables. Panel C shows average adjusted gross income and tax rates for select income percentiles, pooled across states from 1979 to 2008.

Panel A: Summary Statistics for Dependent Variables in Model

Variable	Observations	Mean	SD	Min	Max	Median
Economic Growth						
GDP	1076	37703.91	9019.302	18624.96	69946.16	37450.88
$\Delta \log$ GDP	1076	.0146	.0282	-.109	.1323	.0167
Labor Supply						
E_M	1076	.7933	.0407	.6297	.8983	.7954
ΔE_M	1076	-.0034	.025	-.1077	.1033	-.0035
E_F	1076	.6573	.0646	.409	.8122	.6595
ΔE_F	1076	.0032	.0232	-.0771	.1007	.0035
Small Business Activity						
Estabs	1076	13354.43	12080.97	860	78489	9534
$\Delta \log$ Estabs	1076	.0184	.0268	-.1064	.1331	.0206
Job Creation	1076	.0075	.0252	-.1206	.0999	.0108
Consumption*						
PCE	484	30216.51	4378.859	19320.49	43628.41	29433.85
$\Delta \log$ PCE	448	.015	.0243	-.0769	.077	.0161
PCE_{DG}	484	3870.947	448.656	2674.854	5081.664	3855.947
$\Delta \log PCE_{DG}$	448	-.0031	.0535	-.1721	.1663	.0045
PCE_{NDGS}	484	26345.57	4121.359	15981.81	39472.44	25641.63
$\Delta \log PCE_{NDGS}$	448	.0174	.0222	-.0649	.0915	.0186

All monetary figures are deflated to 2009 US Dollars using the GDP deflator.

* The consumption series is available from BEA for 1997 to 2009; the growth variables are from 1998 to 2009.

The unit of observation is state-year. For more information on sample selection, see Section 1.

Panel B: Summary Statistics for Key Explanatory Variables, Controls, and Instruments in Model						
Variable	Observations	Mean	SD	Min	Max	Median
Key Explanatory Variables						
$C(10)$	1076	.0904	.0235	.0192	.1473	.0924
$C(90)$	1076	.1696	.0238	.0951	.2467	.1696
$C(15)$	1076	.0975	.0253	.02	.1599	.0996
$C(85)$	1076	.1531	.0234	.0827	.231	.1525
$C(20)$	1076	.1043	.0267	.0201	.1749	.1063
$C(80)$	1076	.1449	.0228	.0683	.2353	.1442
$\log C(10)$	1076	-2.4429	.2917	-3.9545	-1.9153	-2.3817
$\log C(90)$	1076	-1.7841	.1425	-2.3525	-1.3995	-1.7743
$\log C(15)$	1076	-2.3664	.2902	-3.9107	-1.8332	-2.3069
$\log C(85)$	1076	-1.8887	.1548	-2.493	-1.4654	-1.8803
$\log C(20)$	1076	-2.2977	.2877	-3.9066	-1.7437	-2.2415
$\log C(80)$	1076	-1.9442	.161	-2.6839	-1.4468	-1.9365
Δ AMTR	1076	.0053	.014	-.0468	.069	.0061
Control Variables						
log GDP	1076	10.4938	.2448	9.843	11.1555	10.5112
$\frac{\text{Income(50)}}{\text{Income(10)}}$	1076	5.9233	.9033	3.2776	10.2265	5.861
$\frac{\text{Income(90)}}{\text{Income(50)}}$	1076	3.1711	.4402	2.3927	8.8194	3.1239
$\log \frac{\text{Income(50)}}{\text{Income(10)}}$	1076	1.7674	.1519	1.1871	2.325	1.7683
$\log \frac{\text{Income(90)}}{\text{Income(50)}}$	1076	1.1459	.1236	.8724	2.177	1.1391
Education	1076	1.4049	.3019	.5246	2.4159	1.4023
Amount of Government Direct General Expenditure per Capita	1076	2383.971	799.5327	920.9448	5854.39	2266.16
Government Expenditure*	1076	-2.773	.2389	-3.3725	-2.0217	-2.7674
Income Growth	1076	.0213	.0206	-.1332	.1727	.0215
$\frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$	1076	5.4836	.5057	4.1431	7.7806	5.4630
$\frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$	1076	2.7051	.1349	2.4368	3.1011	2.7096
$\log \frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$	1076	1.6974	.0936	1.4214	2.0516	1.6980
$\log \frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$	1076	.9939	.0502	.8907	1.1318	.9968
Charity_{1979}	1076	.0154	.0039	.0076	.0397	.0150
Exogenous Instruments						
z_{pi}	1038	-.0619	.2868	-1.0796	.435	0
z_{ci}	1038	-.0374	1.6454	-3.2839	7.3821	0
$z_{pi} \times \log \frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$	1038	-.1059	.489	-1.9774	.7888	0
$z_{pi} \times \log \frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$	1038	-.0613	.2849	-1.1534	.4621	0
$z_{pi} \times \text{Charity}_{1979}$	1038	-.0009	.0046	-.0428	.01	0
$z_{ci} \times \log \frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$	1038	-.0675	2.8037	-6.0146	14.0119	0
$z_{ci} \times \log \frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$	1038	-.0352	1.6421	-3.5081	8.0508	0
$z_{ci} \times \text{Charity}_{1979}$	1038	-.0005	.0259	-.1302	.1693	0
State Senate	1059	.5701	.1813	.1429	1	.5517
State House	1059	.5715	.162	.1571	1	.5667
Governor	1076	.5297	.4993	0	1	1
Elderly	1076	.1232	.0177	.0742	.1821	.1242
Age 5 to 17 population	1076	.1914	.0172	.1352	.2753	.1896
Single Mother	1076	.0659	.0172	.0313	.1502	.0642

Panel C: Mean Income and Tax by Income Percentile								
	i = 10th Pct.	i = 15th Pct.	i = 20th Pct.	i = 50th Pct.	i = 80th Pct.	i = 85th Pct.	i = 90th Pct.	Mean
Income(i)	5247.15	7992.87	10872.94	30619.98	68167.50	79555.99	97287.65	48089.65
Tax(i)	79.32	167.26	314.13	2383.17	7758.68	9799.30	13649.92	6873.15
Income(i) − Tax(i)	5167.83	7825.61	10558.80	28236.81	60408.82	69756.70	83637.72	41216.50
$\frac{\text{Tax}(i)}{\text{Income}(i)}$	.0148	.0204	.0284	.0773	.1145	.1238	.1403	.1408

All monetary figures are in 2009 US Dollars (using GDP deflator).
The unit of observation is state-year. For more information on sample selection, see Section 1.
* Government Expenditure $= \log \frac{\text{Total Amount of Government Direct General Expenditure}}{\text{GDP}}$

Table 3: The Effects of Contraction Factors on State Level GDP Growth

This table shows our regression results for our main specification with state-level real GDP per capita growth as our dependent variable. We look at the log change in GDP per capita, $\Delta \log \text{GDP}_{s,t} = \log \text{GDP}_{s,t} - \log_{s,t-1}$. Column (1) shows OLS estimates with $\log C(10)$ as the only regressor, while Column (2) adds $\log C(90)$ as a regressor. Columns (3) and (4) show our full IV GMM specification results with state and time fixed effects. These columns have coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Column (3) uses our tax shock instruments, Z, and Column (4) uses political and demographic instruments, Z'. The lower panel of the table shows regressions statistics: the use of fixed effects, number of observations, the mean of the dependent variable and log contraction factors, and IV GMM statistics such as autocorrelation tests, Hansen statistic, and number of instruments.

Specification:

$$\Delta \log \text{GDP}_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)

Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	OLS		IV GMM	
Model			Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(10)$	0.008***	0.013***	0.110**	0.083*
	(0.003)	(0.004)	(0.054)	(0.048)
$\log C(90)$		-0.017**	-0.242***	-0.219**
		(0.008)	(0.074)	(0.095)
Δ AMTR			-0.618	-0.405
			(1.637)	(1.726)
log GDP			0.063	-0.016
			(0.069)	(0.053)
$\log \frac{\text{Income}(50)}{\text{Income}(10)}$			0.027	0.024
			(0.019)	(0.027)
$\log \frac{\text{Income}(90)}{\text{Income}(50)}$			0.179*	0.151
			(0.105)	(0.144)
Education			-0.052*	-0.041
			(0.027)	(0.030)
Government Expenditure			-0.014	-0.033
			(0.026)	(0.026)
State FE	N	N	Y	Y
Time FE	N	N	Y	Y
M2 (p-val)			0.125	0.212
Hansen J			7.531	7.857
Hansen (p-val)			0.675	0.448
# Observations	1076	1076	1038	1059
# Instruments			46	45
Means:				
Dep. Variable	0.0146	0.0146	0.0165	0.0145
$\log C(10)$	-2.4429	-2.4429	-2.4280	-2.4404
$\log C(90)$		-1.7841	-1.7776	-1.7830
$C(10)$	0.0904	0.0904	0.0915	0.0906
$C(90)$		0.1696	0.1706	0.1698

Significance Levels: * 10% ** 5% *** 1%

OLS standard errors are clustered at the state level. IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 4: The Effects of Contraction Factors on Changes in Employment Rate

This table shows our regression results for our labor supply mechanism with changes in employment rate as our dependent variable. Using the March Current Population Survey, we look at the change in employment rate, $\Delta Es,t = E_{s,t} - E_{s,t-1}$, separately for males and females among 18 to 64 year olds. All four columns use full IV GMM specification results with state and time fixed effects, showing coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Columns (1) and (2) have male employment as the dependent variable, whereas Columns (3) and (4) have female employment as the dependent variable. Columns (1) and (3) use tax shock instruments, Z, and Columns (2) and (4) use political and demographic instruments, Z'.

Specification:

$$\Delta E_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)

Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	Males		Females	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(10)$	0.017	0.048	0.101**	0.052
	(0.056)	(0.041)	(0.043)	(0.048)
$\log C(90)$	-0.083	-0.105	-0.186*	-0.190**
	(0.090)	(0.078)	(0.101)	(0.093)
Δ AMTR	-1.247	-2.008	1.031	-0.411
	(0.862)	(1.445)	(1.174)	(1.842)
log GDP	0.012	0.045	-0.057	0.015
	(0.061)	(0.053)	(0.063)	(0.051)
$\log \frac{\text{Income(50)}}{\text{Income(10)}}$	0.004	0.018	-0.004	0.004
	(0.017)	(0.022)	(0.013)	(0.037)
$\log \frac{\text{Income(90)}}{\text{Income(50)}}$	0.109*	0.193*	0.014	0.095
	(0.062)	(0.107)	(0.063)	(0.137)
Education	-0.025	-0.038	-0.005	-0.031
	(0.027)	(0.024)	(0.026)	(0.023)
Government Expenditure	-0.016	-0.018	-0.022	-0.016
	(0.033)	(0.022)	(0.034)	(0.034)
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
M2 (p-val)	0.286	0.571	0.575	0.689
Hansen J	10.009	2.871	7.278	11.118
Hansen (p-val)	0.440	0.942	0.699	0.195
# Observations	1038	1059	1038	1059
# Instruments	46	45	46	45
Means:				
Dep. Variable	-0.0018	-0.0034	0.0041	0.0033
$\log C(10)$	-2.4280	-2.4404	-2.4280	-2.4404
$\log C(90)$	-1.7776	-1.7830	-1.7776	-1.7830
$C(10)$	0.0915	0.0906	0.0915	0.0906
$C(90)$	0.1706	0.1698	0.1706	0.1698

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 5: The Effects of Contraction Factors on Small Business

This table shows our regression results for our business activity mechanism with small business growth rate as our dependent variable. We look at the growth rate in the establishments of size 20 to 49, $\Delta \log \text{Estabs}_{s,t} = \log \text{Estabs}_{s,t} - \log \text{Estabs}_{s,t-1}$, as well as net job creation for continuing establishments, which is defined as jobs created less jobs lost scaled by a two year moving average of employment. All four columns use full IV GMM specification results with state and time fixed effects, showing coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Columns (1) and (2) have establishment growth rate as the dependent variable, whereas Columns (3) and (4) have net job creation rate as the dependent variable. Columns (1) and (3) use tax shock instruments, Z, and Columns (2) and (4) use political and demographic instruments, Z'.

Specification:

$\Delta \log \text{Estabs}_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)
Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	Small Business Growth		Job Creation	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(10)$	0.073*	0.086	0.069	0.095**
	(0.043)	(0.078)	(0.073)	(0.041)
$\log C(90)$	-0.227***	-0.194***	-0.051	-0.132**
	(0.042)	(0.051)	(0.065)	(0.066)
Δ AMTR	-0.753	-2.535	-0.830	-3.015**
	(1.272)	(3.838)	(1.095)	(1.335)
log GDP	0.056	0.040	-0.049	-0.024
	(0.048)	(0.040)	(0.048)	(0.047)
$\log \frac{\text{Income}(50)}{\text{Income}(10)}$	0.010	0.026	-0.015	0.018
	(0.015)	(0.048)	(0.024)	(0.022)
$\log \frac{\text{Income}(90)}{\text{Income}(50)}$	0.166**	0.292	0.094	0.306***
	(0.083)	(0.247)	(0.088)	(0.105)
Education	-0.014	-0.037	-0.008	-0.031
	(0.021)	(0.033)	(0.025)	(0.024)
Government Expenditure	-0.029	-0.058**	-0.072***	-0.081***
	(0.029)	(0.023)	(0.025)	(0.019)
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
M2 (p-val)	0.123	0.236	0.423	0.353
Hansen J	9.324	5.351	17.460	4.921
Hansen (p-val)	0.502	0.719	0.065	0.766
# Observations	1038	1059	1038	1059
# Instruments	46	45	46	45
Means:				
Dep. Variable	0.0199	0.0186	0.0096	0.0075
$\log C(10)$	-2.4280	-2.4404	-2.4280	-2.4404
$\log C(90)$	-1.7776	-1.7830	-1.7776	-1.7830
$C(10)$	0.0915	0.0906	0.0915	0.0906
$C(90)$	0.1706	0.1698	0.1706	0.1698

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 6: The Effects of Log Contraction Factors on Personal Consumption Growth

This table shows our regression results for our consumption mechanism with personal consumption growth rate as our dependent variable. We look at consumption growth rate for various categories, $\Delta \log \text{PCE}_{s,t} = \log \text{PCE}_{s,t} - \log \text{PCE}_{s,t-1}$. All six columns use full IV GMM specification results with state and time fixed effects, showing coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, state government direct general expenditures, and state personal income growth. Columns (1) and (2) have growth rates for total personal consumption as the dependent variable, Columns (3) and (4) have durable goods consumption growth as the dependent variable, and Columns (5) and (6) have nondurable goods and services consumption growth as the dependent variable. Columns (1), (3), and (5) use tax shock instruments, Z, and Columns (2), (4), and (6) use political and demographic instruments, Z'.

Specification:

$$\Delta \log \text{PCE}_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)
Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	Personal Consumption		Durable Goods		Nondurable Goods & Services	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\log C(10)$	0.039**	0.029*	0.032	0.029	0.039**	0.028**
	(0.017)	(0.016)	(0.027)	(0.019)	(0.015)	(0.014)
$\log C(90)$	0.129	-0.021	0.198	-0.009	0.107	-0.029
	(0.085)	(0.042)	(0.134)	(0.076)	(0.084)	(0.030)
Δ AMTR	-0.976**	-0.408	-0.985	-0.672	-0.841*	-0.479
	(0.472)	(0.580)	(0.616)	(0.706)	(0.448)	(0.452)
$\log \frac{\text{Income(50)}}{\text{Income(10)}}$	0.005	0.006	0.014	0.014	0.001	0.006
	(0.017)	(0.016)	(0.021)	(0.028)	(0.016)	(0.011)
$\log \frac{\text{Income(90)}}{\text{Income(50)}}$	0.004	0.042	-0.026	0.070	0.004	0.051
	(0.057)	(0.046)	(0.098)	(0.071)	(0.058)	(0.036)
log GDP	-0.090**	0.013	-0.125**	-0.016	-0.085**	0.015
	(0.041)	(0.043)	(0.053)	(0.055)	(0.039)	(0.031)
Education	0.023	0.002	0.045	0.021	0.024	-0.004
	(0.022)	(0.017)	(0.037)	(0.025)	(0.020)	(0.016)
Government Expenditure	0.009	0.016	0.014	0.007	0.006	0.011
	(0.021)	(0.014)	(0.023)	(0.016)	(0.025)	(0.013)
Income Growth	0.618***	0.677***	0.764***	0.890***	0.595***	0.711***
	(0.140)	(0.146)	(0.219)	(0.209)	(0.157)	(0.128)
State FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
M2 (p-val)	0.164	0.165	0.673	0.384	0.298	0.148
Hansen J	23.085	25.640	26.895	29.578	23.689	28.479
Hansen (p-val)	0.456	0.539	0.260	0.333	0.421	0.387
# Observations	410	437	410	437	410	437
# Instruments	43	48	43	48	43	48
Means:						
Dep. Variable	0.0195	0.0149	0.0047	-0.0031	0.0215	0.0173
$\log C(10)$	-2.6226	-2.6390	-2.6226	-2.6390	-2.6226	-2.6390
$\log C(90)$	-1.8491	-1.8570	-1.8491	-1.8570	-1.8491	-1.8570
$C(10)$	0.0754	0.0742	0.0754	0.0742	0.0754	0.0742
$C(90)$	0.1590	0.1579	0.1590	0.1579	0.1590	0.1579

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 7: Robustness 1 - The Effects of Log Contraction Factors on State Level GDP Growth

This table provides a robustness test to our main regression and has state GDP growth as the dependent variable. Overall the specification is the same, but we use different percentiles of the contraction factor. All four columns use full IV GMM specification results with state and time fixed effects, showing coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Columns (1) and (2) use contraction factors with the 15th percentile representing below median and the 85th percentile representing above median, whereas Columns (3) and (4) use contraction factors with the 20th percentile representing below median and the 80th percentile representing above median. Columns (1) and (3) use tax shock instruments, Z, and Columns (2) and (4) use political and demographic instruments, Z'.

Specification:

$$\Delta \log \text{GDP}_{s,t} = \kappa_1 \log C_{s,t-1}(i) + \kappa_2 \log C_{s,t-1}(j) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)
Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	Using $\log C(15)$ & $\log C(85)$		Using $\log C(20)$ & $\log C(80)$	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(15)$	0.089*	0.086		
	(0.048)	(0.056)		
$\log C(85)$	-0.223***	-0.279***		
	(0.057)	(0.083)		
$\log C(20)$			0.064	0.036
			(0.040)	(0.041)
$\log C(80)$			-0.192***	-0.142***
			(0.054)	(0.048)
Δ AMTR	-1.271	-1.873	-1.913	-1.223
	(1.516)	(2.187)	(1.328)	(2.028)
log GDP	0.055	0.033	0.087	0.004
	(0.065)	(0.059)	(0.069)	(0.047)
$\log \frac{\text{Income}(50)}{\text{Income}(10)}$	0.019	0.022	0.015	0.008
	(0.021)	(0.029)	(0.017)	(0.023)
$\log \frac{\text{Income}(90)}{\text{Income}(50)}$	0.177	0.211	0.159	0.086
	(0.114)	(0.152)	(0.105)	(0.127)
Education	-0.045	-0.054	-0.044	-0.031
	(0.028)	(0.036)	(0.027)	(0.027)
Government Expenditure	-0.023	-0.018	-0.003	-0.010
	(0.027)	(0.030)	(0.033)	(0.030)
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
M2 (p-val)	0.233	0.397	0.267	0.340
Hansen J	4.511	4.235	7.592	7.105
Hansen (p-val)	0.921	0.835	0.669	0.525
# Observations	1038	1059	1038	1059
# Instruments	46	45	46	45
Means:				
Dep. Variable	0.0165	0.0145	0.0165	0.0145
$\log C(15), \log C(20)$	-2.3514	-2.3639	-2.2835	-2.2952
$\log C(85), \log C(80)$	-1.8816	-1.8876	-1.9366	-1.9435
$C(15), C(20)$	0.0987	0.0977	0.1056	0.1046
$C(85), C(80)$	0.1541	0.1532	0.1459	0.1450

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 8: Robustness 2 - The Effects of Log Contraction Factors on State Level GDP Growth

This table provides another robustness test to our main regression and has state GDP growth as the dependent variable. Overall the specification is the same, but for one alteration we use an additional control, and for the other alteration we use a different income distributions to calculate our original contraction factors, $C(10), C(90)$. All four columns use full IV GMM specification results with state and time fixed effects, showing coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Columns (1) and (2) introduces the lagged unemployment rate in addition to our existing controls. Columns (3) and (4) uses our original specification, but uses the market income distribution instead to calculate contraction factors and income ratios. Columns (1) and (3) use tax shock instruments, Z, and Columns (2) and (4) use political and demographic instruments, Z'.

Specification:

$$\Delta \log \text{GDP}_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)
Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	Unemployment Rate		Market Income Distribution	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(10)$	0.082	0.060**		
	(0.077)	(0.028)		
$\log C(90)$	-0.244***	-0.149**		
	(0.069)	(0.066)		
$\log C(10)$			0.142***	0.092*
			(0.042)	(0.053)
$\log C(90)$			-0.141**	-0.210**
			(0.067)	(0.085)
Δ AMTR	0.242	0.306	-1.832	-0.814
	(1.911)	(1.051)	(1.513)	(1.753)
log GDP	0.018	-0.044	0.008	-0.017
	(0.139)	(0.036)	(0.054)	(0.050)
$\log \frac{\text{Income(50)}}{\text{Income(10)}}$	0.014	0.016		
	(0.024)	(0.019)		
$\log \frac{\text{Income(90)}}{\text{Income(50)}}$	0.121	0.076		
	(0.149)	(0.079)		
$\log \frac{\text{Income(50)}}{\text{Income(10)}}$			0.036**	0.021
			(0.017)	(0.022)
$\log \frac{\text{Income(90)}}{\text{Income(50)}}$			0.213**	0.171
			(0.092)	(0.146)
Education	-0.035	-0.039***	-0.048**	-0.044
	(0.069)	(0.014)	(0.020)	(0.031)
Government Expenditure	-0.010	-0.030	-0.016	-0.023
	(0.079)	(0.022)	(0.025)	(0.027)
Unemployment Rate	-0.419	-0.412***		
	(0.338)	(0.098)		
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
M2 (p-val)	0.140	0.156	0.120	0.118
Hansen J	5.256	6.378	5.314	7.112
Hansen (p-val)	0.918	0.702	0.947	0.525
# Observations	1038	1059	1038	1059
# Instruments	48	47	48	45
Means:				
Dep. Variable	0.0165	0.0145	0.0165	0.0145
$\log C(10)$	-2.4280	-2.4404	-2.4133	-2.4245
$\log C(90)$	-1.7776	-1.7830	-1.7707	-1.7760
$C(10)$	0.0915	0.0906	0.0927	0.0918
$C(90)$	0.1706	0.1698	0.1718	0.1710

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 9: Robustness 3 - The Effects of Log Contraction Factors on State Level GDP Growth

This table provides a final robustness test to our main regression and has state GDP growth as the dependent variable. Overall the specification is the same, but we add different controls for each set. All six columns use full IV GMM specification results with state and time fixed effects, showing coefficients for both log contraction factors, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Columns (1) and (2) add lagged state personal income growth as a control, while Columns (3) and (4) use state government public welfare expenditure as an additional control. Columns (1) and (3) use tax shock instruments, Z, and Columns (2) and (4) use political and demographic instruments, Z'.

Specification:

$$\Delta \log \mathrm{GDP}_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \mathrm{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)
Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

Additional Controls	Personal Income Growth		Public Welfare Expenditure	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(10)$	0.089*	0.074*	0.103*	0.067**
	(0.048)	(0.045)	(0.062)	(0.028)
$\log C(90)$	-0.277***	-0.181*	-0.232***	-0.139**
	(0.082)	(0.109)	(0.088)	(0.067)
Δ AMTR	0.704	-0.034	0.256	-0.243
	(1.363)	(1.403)	(1.646)	(1.231)
log GDP	0.048	-0.024	0.024	-0.026
	(0.068)	(0.044)	(0.051)	(0.034)
$\log \frac{\text{Income}(50)}{\text{Income}(10)}$	0.015	0.021	0.018	0.018
	(0.016)	(0.024)	(0.022)	(0.017)
$\log \frac{\text{Income}(90)}{\text{Income}(50)}$	0.104	0.103	0.110	0.099
	(0.096)	(0.136)	(0.105)	(0.086)
Education	-0.043	-0.033	-0.039	-0.039**
	(0.027)	(0.028)	(0.027)	(0.018)
Government Expenditure	-0.016	-0.023	-0.030	-0.048*
	(0.023)	(0.022)	(0.028)	(0.027)
Income Growth	0.120	0.113		
	(0.151)	(0.123)		
Government Welfare Exp. Share			-0.034	-0.077
			(0.081)	(0.058)
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
M2 (p-val)	0.243	0.313	0.146	0.226
Hansen J	8.458	7.760	9.056	7.544
Hansen (p-val)	0.672	0.559	0.617	0.581
# Observations	1038	1059	1038	1059
# Instruments	48	47	48	47
Means:				
Dep. Variable	0.0165	0.0145	0.0165	0.0145
$\log C(10)$	-2.4280	-2.4404	-2.4280	-2.4404
$\log C(90)$	-1.7776	-1.7830	-1.7776	-1.7830
$C(10)$	0.0915	0.0906	0.0915	0.0906
$C(90)$	0.1706	0.1698	0.1706	0.1698

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Table 10: Robustness 4 - The Effects of Alternative Contraction Factors on State Level GDP Growth

This table provides a robustness test to our main regression by using alternate definitions of inequality reduction and has state GDP growth as the dependent variable. For Columns (1) and (2), we use the national income distribution to calculate contraction factors, rather than the state income distributions. For Columns (3) and (4), we use an alternative inequality reduction measure detailed below. All four columns use full IV GMM specification results with state and time fixed effects, showing coefficients for inequality reduction, while controlling for lagged GDP per capita, changes in average marginal tax rates, income ratios, education, and state government direct general expenditures. Columns (1) and (3) use tax shock instruments, Z, and Columns (2) and (4) use political and demographic instruments, Z'.

Specification:

$$\Delta \log \text{GDP}_{s,t} = \kappa_1 \log C_{s,t-1}(10) + \kappa_2 \log C_{s,t-1}(90) + \gamma \Delta AMTR_{s,t-1} + h_1 \log \frac{Income_{s,t-1}(50)}{Income_{s,t-1}(10)} + h_2 \log \frac{Income_{s,t-1}(90)}{Income_{s,t-1}(50)} + \alpha \log \text{GDP}_{s,t-1} + X_{s,t-1}\beta + \delta_s + \eta_t + \varepsilon_{s,t}$$

$$\text{Inequality Reduction(90)} = \left(\log \frac{\text{Income(90)}}{\text{Income(50)}} - \log \frac{\text{Income(90)}-\text{Tax(90)}}{\text{Income(50)}-\text{Tax(50)}}\right) / \left(\log \frac{\text{Income(90)}}{\text{Income(50)}}\right) \times 100$$

$$\text{Inequality Reduction(10)} = \left(\log \frac{\text{Income(50)}}{\text{Income(10)}} - \log \frac{\text{Income(50)}-\text{Tax(50)}}{\text{Income(10)}-\text{Tax(10)}}\right) / \left(\log \frac{\text{Income(50)}}{\text{Income(10)}}\right) \times 100$$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)

Z': Political affiliation and demographic instruments (majority of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	Contraction Factors Based on National Income Distribution		Alternative Measure of Inequality Reduction (IR)	
Model	Z + Time FE	Z' + Time FE	Z + Time FE	Z' + Time FE
Regressors	(1)	(2)	(3)	(4)
$\log C(10)$	0.144*	0.141		
	(0.083)	(0.108)		
$\log C(90)$	-0.308**	-0.288**		
	(0.122)	(0.128)		
Inequality Reduction(10)			0.014	0.005
			(0.013)	(0.015)
Inequality Reduction(90)			-0.017**	-0.022**
			(0.009)	(0.009)
Δ AMTR	0.146	-0.481	-0.825	-1.676
	(1.084)	(2.102)	(1.360)	(2.786)
log GDP	-0.030	-0.032	-0.003	0.014
	(0.078)	(0.048)	(0.059)	(0.051)
$\log \frac{\text{Income(50)}}{\text{Income(10)}}$	0.007	0.014	0.031	0.032
	(0.014)	(0.032)	(0.030)	(0.049)
$\log \frac{\text{Income(90)}}{\text{Income(50)}}$	0.010	0.057	0.117	0.191
	(0.079)	(0.144)	(0.075)	(0.166)
Education	-0.043	-0.061*	-0.047**	-0.059*
	(0.031)	(0.032)	(0.023)	(0.031)
Government Expenditure	-0.022	-0.033	-0.032*	-0.039
	(0.032)	(0.029)	(0.019)	(0.024)
State FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
M2 (p-val)	0.417	0.311	0.158	0.330
Hansen J	8.248	8.017	4.083	10.837
Hansen (p-val)	0.605	0.432	0.944	0.211
# Observations	1038	1059	1038	1059
# Instruments	46	45	46	45
Means:				
Dep. Variable	0.0165	0.0145	0.0165	0.0145
$\log C(10)$	-2.4032	-2.4181		
$\log C(90)$	-1.7618	-1.7679		
Inequality Reduction(10)			3.7931	3.7507
Inequality Reduction(90)			6.1913	6.1736

Significance Levels: * 10% ** 5% *** 1%

IV GMM model uses robust, two step System GMM estimator with Windmeijer-corrected standard errors.

Figure 1: Pre-Tax and Post-Tax Income Distribution

This figure shows the distribution, mean, and standard deviations of the logs of pre-tax and post-tax income across income groups in all states from 1979 to 2008. The figure is shown from the 5th to 95th percentile of the pre-tax log income distribution to better see the compression in the distribution caused by progressive taxation. The means and standard deviations shown are for the entire national income distribution.

Figure 2: Contraction Factor Distribution

This figure shows the distribution of contraction factors that cover all states from 1979 to 2008.

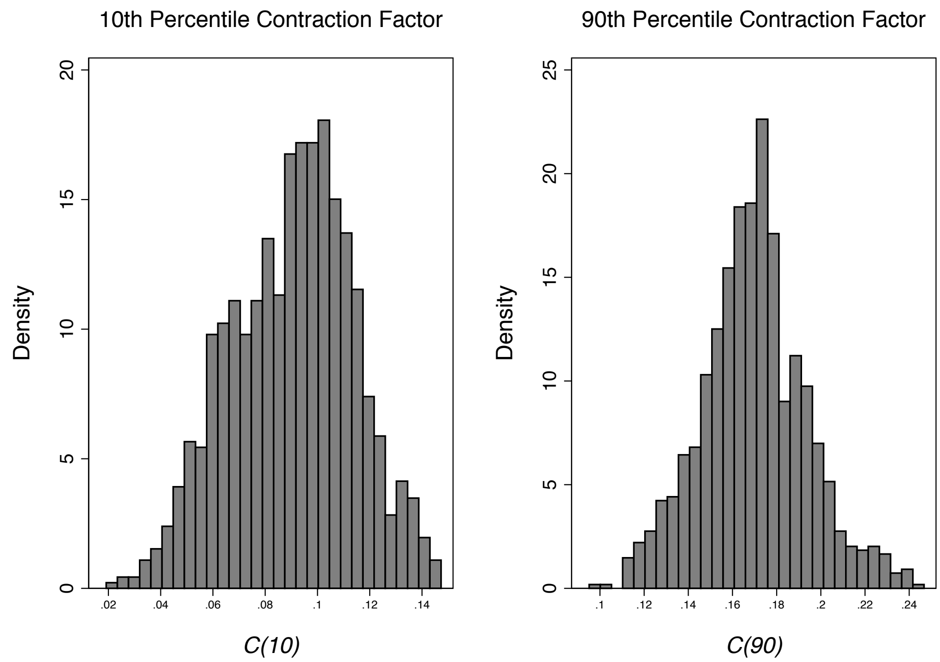
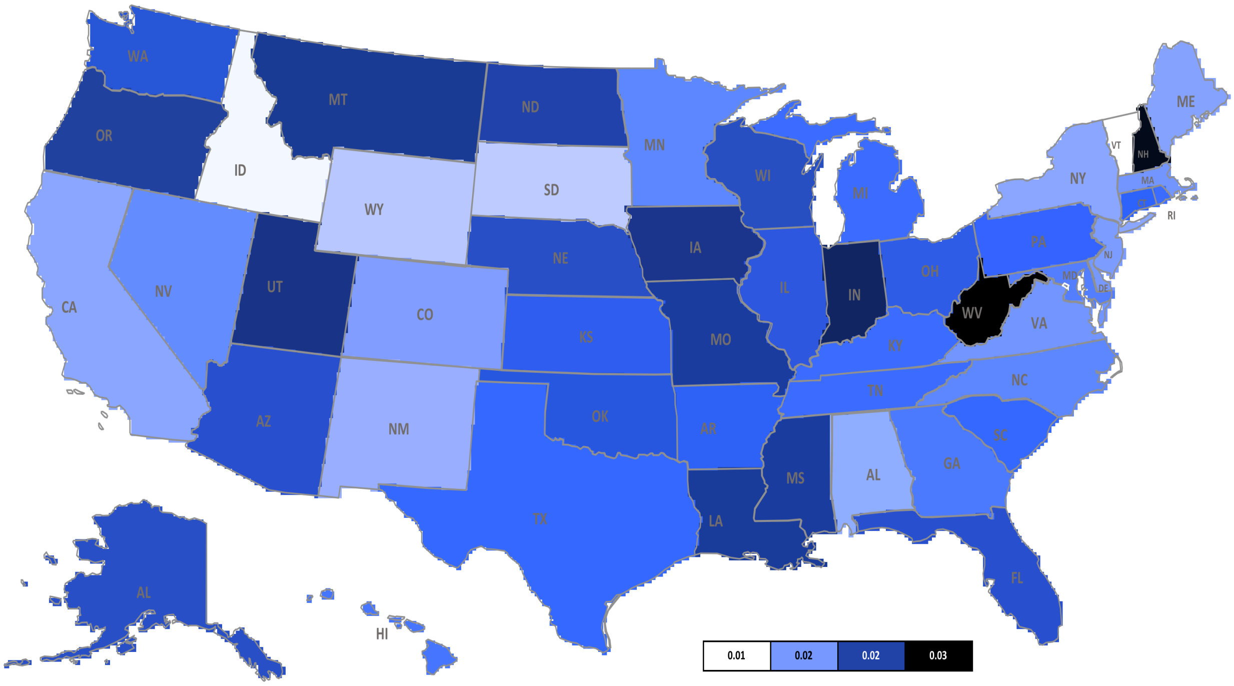
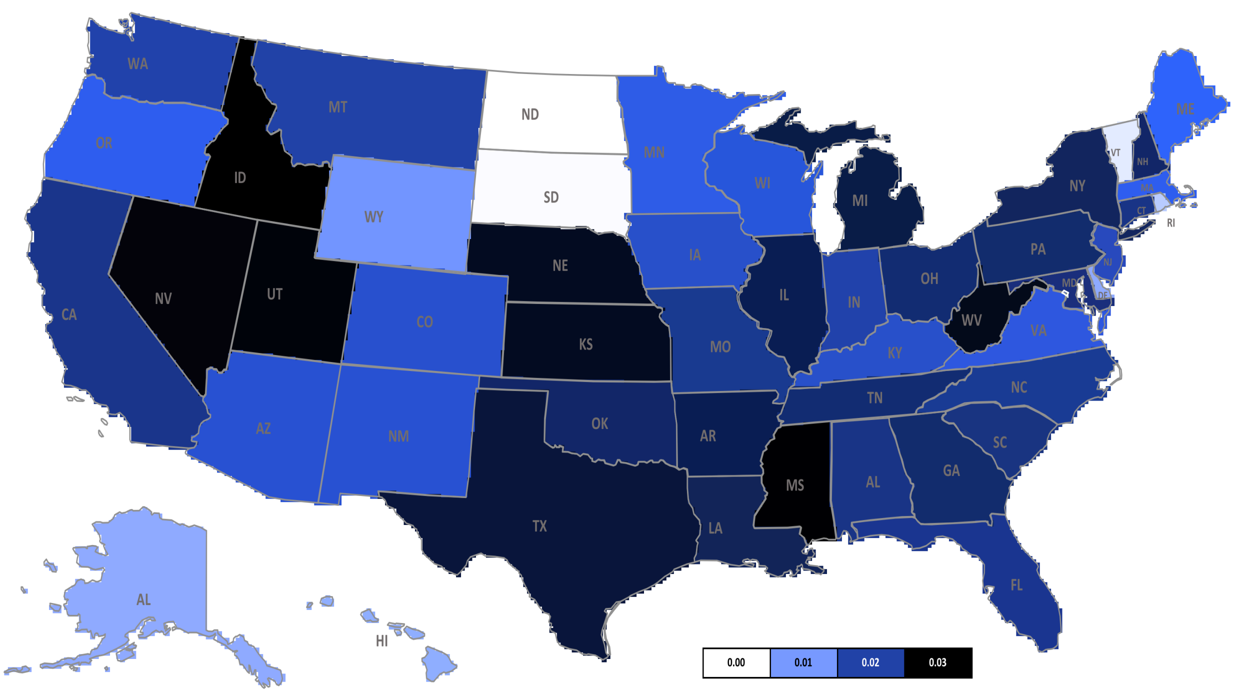


Figure 3: Contraction Factors across States: Standard Deviation

This figure illustrates the state standard deviations for both contraction factors, $C(90)$ and $C(10)$. The darker states represent a higher variation in contraction factor.



(a) Contraction factor $C(90)$



(b) Contraction factor $C(10)$

Figure 4: Average Marginal Tax Rate Distribution

This figure shows the distribution of average marginal tax rates based on the state income distributions from 1979 to 2008.

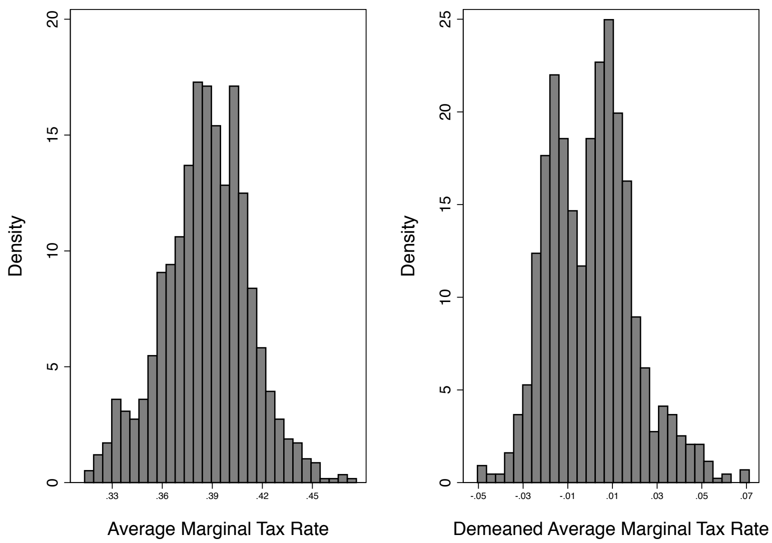


Figure 5: State Tax Rate Distribution

This figure shows the distribution of state average personal income tax rate factors that cover all states from 1979 to 2008.

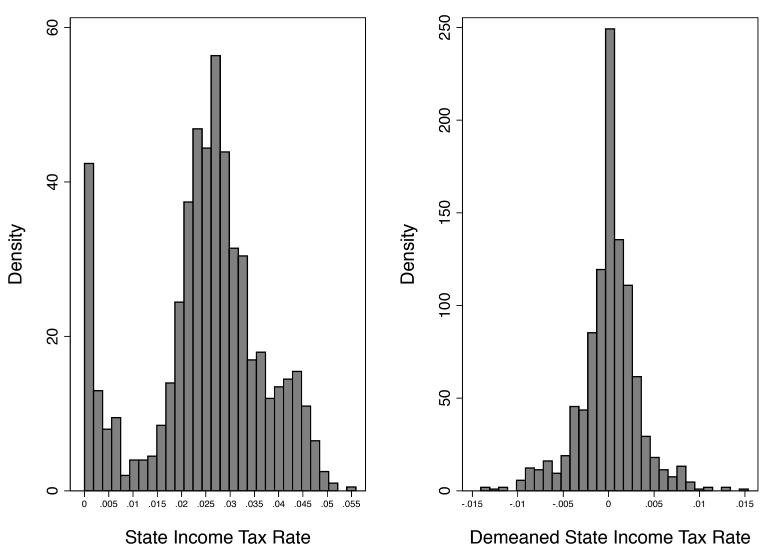


Figure 6: Number of States with State EITC Program

This figure shows the number of states in a given year that have a refundable state EITC program over our sample period from 1979 to 2008.

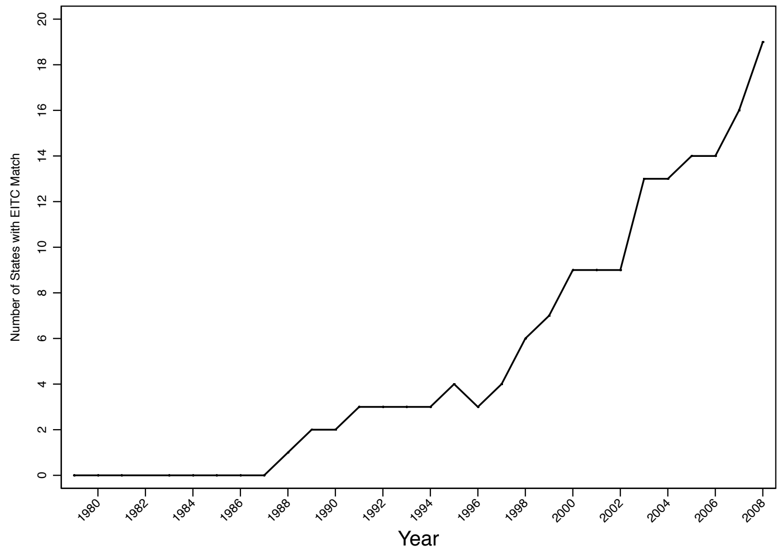
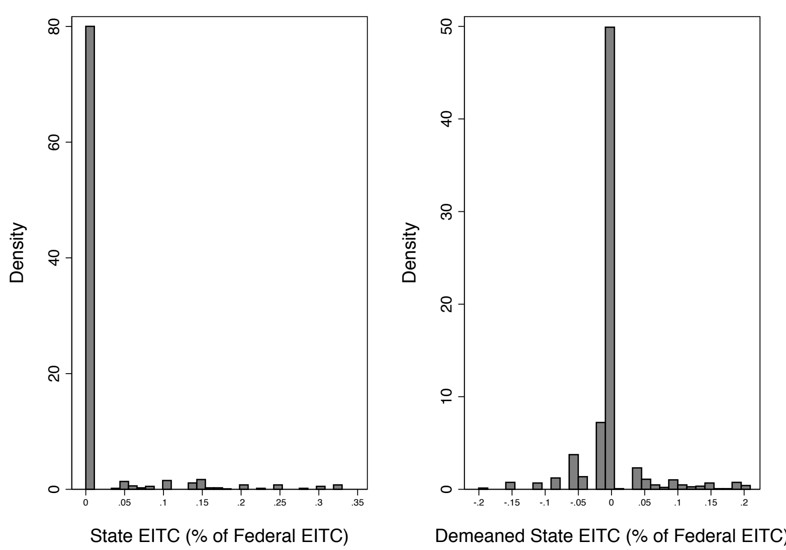


Figure 7: State EITC Match Distribution

This figure shows the distribution of state refundable EITC match (as % of federal EITC) for our sample period from 1979 to 2008. The state EITC match rates differ by family structure. Here we only plot the matching rate for a two-child household.



Appendix: For Review and Online Publication Only

A Tax Definitions

The IRS provides detailed definitions for total tax liability for every year it publishes a report. Below are the definitions from 1979 and 2008, the first and last years in our current panel of data.

In 1979, total tax liability was the sum of income tax after credits, the additional tax for tax preferences, self-employment tax, social security tax on tips, tax from recomputing prior-year investment credit, taxes from individual retirement arrangements, and other taxes, reduced by the earned income credit used to offset all other taxes.

In 2008, total tax liability was the sum of income tax after credits, self-employment tax, social security and Medicare tax on tips, additional tax on HSA and MSA distributions, tax from recapturing prior-year investment credits, low-income housing credit, qualified electric vehicle credit, Indian employment credit, new market credit, employer-provided child care facilities credit, alternative motor vehicle credit, alternative fuel vehicle refueling property credit, tax from recapture of federal mortgage subsidy, taxes from qualified plans (including individual retirement accounts) and other tax-favoured accounts, Section 72 penalty taxes, household employment taxes, tax on golden parachute payments, Form 4970 tax, excise tax on insider stock compensation from an expatriated corporation, and interest on tax due on installment income from sale of residential lot and time-shares. These taxes are then reduced by the earned income credit used to offset all other taxes, first-time homebuyer credit, recovery rebate credit and the refundable prior year minimum tax credit, limited to zero. For the statistics, unlike the Form 1040, total tax liability does not include any advance earned income credit payments.

B Additional Data Description

B.1 TAXSIM data

Our data on tax returns is the TAXSIM microdata from NBER. It has been prepared by the Statistics of Income Division of the Internal Revenue Service (IRS) for public use. TAXSIM data is a large stratified random sample of total $3,544,410$ actual tax returns from the IRS administrative records for each state and for each year from 1979 to 2008 (except 1982, where total tax liability is not available). It contains detailed information on Form 1040, such as adjusted gross income, total federal and state tax liability, and tax credits.[37] We use adjusted gross income (AGI) as our measure of pre-tax income (hereafter referred to as "income"), which is defined by the IRS as total income (line 22, Form 1040) minus statutory adjustments

[37] The IRS does not identify the state for the returns with above \$$200,000$ adjusted gross income. NBER reassigns these records to states, such that the number of those returns by state matches figures provided by the Joint Committee on Taxation. However, since our top income bracket is the 90th percentile, which does not cross \$$200,000$ of income in the sample, this issue is not a concern.

(lines 23 through 36, Form 1040).[38] The total tax liability (hereafter "tax") includes all income tax after credits, self-employment tax, and any tax adjustments from previous years. A detailed description of all the components of tax according to the IRS is in Section A of the Appendix.

B.2 Dependent Variables

GDP Growth

The primary dependent variable in our analysis is the state-level log change in real GDP per capita ($\log \text{GDP}_{s,t} - \log \text{GDP}_{s,t-1}$). The state-level real GDP is the state-level real chained GDP in 2009 dollars from BEA. First we use the BEA's interactive data tool for regional data to acquire the relevant data series for annual GDP by state: "Real GDP in chained dollars" and "Quantity indexes for real GDP".[39] The first series in 2009 dollars is available from 1997 to 2009. The real GDP in chained 1997 dollars series is available for each state from 1987 to 1997, while the quantity indexes are available from 1977 onwards. Since the percent change in quantity indexes equals the percent change in real GDP, we are able to use the quantity indexes to extend our state GDP series in 1997 dollars back to 1980, our earliest year of interest. We then convert the pre-1997 real chained GDP series from 1997 dollars to 2009 chained dollars by using the ratio of 2009 dollar GDP to 1997 dollar GDP in 1997, where both series are available. The BEA data tool also has data on annual state personal income, where we use table SA1 to gather state-level population estimates for each year from 1980 to 2009, which use to create GDP per capita, and consequently the annual log change in GDP per capita.

Labour Supply

We also investigate how contraction factors impact economic growth through several mechanisms. First, we collect data on the labour supply mechanism from the CPS through the Integrated Public Use Microdata Series (IPUMS-CPS).[40] Specifically, we use the March samples to collect demographic, state (variable *statefip*), and employment status (variable *empstat*) for individuals from 1980 to 2009. We further restrict our sample to working age individuals, from age 18 to 64. The employment status variable (*empstat*) asks respondents about their work status from the previous week – we consider those that responded with "at work" or "has a job, not at work last week" as employed. Using this variable we separately create average employment rates for males (E_M) and females (E_F) for each state and year. For the final estimation, the first difference of these two variables enter as the dependent variable ($\Delta E_{s,t} = E_{s,t} - E_{s,t-1}$).

[38] Total income consists of all positive sources of income less negative amounts, including wages and salary, taxable interest and dividends, net income from a business, etc. Statutory adjustments include educator expenses, certain business expenses, health savings account deduction, moving expenses, IRA deductions, etc.

[39] See http://www.bea.gov/itable.

[40] See https://cps.ipums.org/cps-action/variables/group.

Small Business Activity

The second mechanism of economic growth that we consider is small business activity. We use the Business Dynamics Statistics (BDS) database, which is available through the US Census Bureau website,[41] to collect state-level data on small businesses from 1980 to 2009. Specifically, we use the file for "Establishment size by state". In the data, small businesses are referred to as establishments, which is a fixed physical location where economic activity occurs. We focus our attention on the number of establishments (variable *estabs*) of size 20 to 49. We then investigate the state-level growth rate of the number of establishments ($\Delta \log \text{Estabs}_{s,t} = \log \text{Estabs}_{s,t} - \log \text{Estabs}_{s,t-1}$). We also consider net job creation rate among those establishments that continued to stay in business from the previous year. The data has variables for number of jobs created (variable *job_creation_continuers*) and jobs lost (variable *job_destruction_continuers*) for continuing establishments. We take the difference of these two variables to get net job creation, and then scale it by the Davis-Haltiwanger-Schuh denominator (variable *denom*), which is a two-year moving average of total employment, to arrive at our net job creation rate variable.

Consumption

The last economic growth mechanism we consider is personal consumption expenditures per capita (PCE). Once again we use the interactive BEA data tool to acquire nominal consumption, data series "Personal consumption expenditures by state", for several categories for each state from 1997 to 2009. In the data, the categories variable is named *linenumber*, which we will use to reference our chosen categories. We deflate the nominal consumption by the GDP deflator and use the same population denominator from real GDP per capita to calculate average real PCE per capita in each state for total consumption (*linenumber* 1), consumption of durable goods (*linenumber* 3), and consumption of nondurable goods and services (sum of *linenumber* 8 and 13). The final estimation uses consumption growth rates, which we calculate using the changes of log consumption ($\Delta \log \text{PCE}_{s,t} = \log \text{PCE}_{s,t} - \log \text{PCE}_{s,t-1}$).

B.3 Explanatory Variables

Our main explanatory variables in the two specifications are one period lagged log contraction factors. We focus on the effect of reducing income inequality between the 10th percentile household and the median household ($\log C_{s,t-1}(10)$) and the effect of reducing income inequality between the 90th percentile household and the median household ($\log C_{s,t-1}(90)$) on our various dependent variables. In addition, we add several control variables based on previous literature.

[41] See https://www.census.gov/ces/dataproducts/bds/data_estab.html.

Contraction Factors

We use the TAXSIM tax return data to construct contraction factors at different income percentiles for each state and for each year from 1979 to 2008.[42] In a given year, using the state income distribution for each state, we create a 10 percentile income bracket centred around the state's pre-tax income percentile i. We then calculate the state-level average tax liabilities associated with the income percentile i by averaging all tax liabilities associated with incomes that fall within the specified 10 percentile state income band. Finally, we calculate contraction factors using Equation 1.

Marginal Tax Rates

Using the TAXSIM micro tax return data as an input, we utilise NBER's TAXSIM simulation program to compute overall marginal tax rates (the sum of federal, state, and FICA tax) for each return, and then calculate the average marginal tax rate $\text{AMTR}_{s,t-1}$.[43] Furthermore, similar to Barro and Redlick (2011), we fix the year of the income distribution, and calculate average marginal tax rate changes based on that one income distribution. Specifically, changes in average marginal tax rate, $\Delta\text{AMTR}_{s,t-1} = \text{AMTR}_{s,t-1} - \text{AMTR}_{s,t-2}$, uses the $t-1$ state income distribution to calculate average marginal tax rates for both $t-1$ and $t-2$. This strategy eliminates any shifts in income distribution that might move a household into a different tax bracket, and helps ensure that the changes in average marginal tax rates are specifically due to changes in tax policies. Table D2 summarises state-level GDP, contraction factors, and changes in AMTR for the 49 states in our analysis.

State Inequality Measures

To control for the previous year's level of inequality within each state, we use the TAXSIM state income distribution in calculating two ratios measuring the 50th percentile income in comparison to the 10th percentile income ($\frac{\text{Income}(50)}{\text{Income}(10)}$), and the 90th percentile income in comparison to the 50th percentile income ($\frac{\text{Income}(90)}{\text{Income}(50)}$). In our specification we use the logs of these ratios ($\log \frac{\text{Income}(50)}{\text{Income}(10)}$, $\log \frac{\text{Income}(90)}{\text{Income}(50)}$).

State Human Capital

We also control for the level of schooling in each state as a measure of the human capital stock. Specifically, we use the CPS data (IPUMS-CPS) to calculate the average years of higher education for all states from 1979 to 2008, which we define as schooling beyond high school (12 years of education). We begin with CPS

[42] Data from 1982 is not included as tax liability is not available in the microdata. We exclude Washington D.C. because it is not a state. We also exclude Alaska from our analysis due to small sample size and large differences between the moments of TAXSIM data and IRS full SOI sample. Finally, for each state, we restrict our analysis to the years that the state has at least 500 tax return observations in the TAXSIM data. Table D1 reports the number of years available from TAXSIM data based on our sample selection criteria.

[43] We utilise the TAXSIM model's "wages" option to calculate marginal tax rates. The average marginal tax rate is calculated using both microdata sampling weights and adjusted gross income as weights.

variable on educational attainment, *educ*, and convert it into a numerical years of schooling variable. For most cases, this is a one to one transformation (for example, $educ =$ Grade 9). In other cases, *educ* contains multiple years (for example, $educ =$ Grade 5 or 6). In that case, we take the midpoint of the range of grades, 5.5. We then create years of higher education for individuals as years of schooling − 12, assigning those with 12 or fewer years of schooling with a value of 0. We also restrict the sample to individuals between 25 and 64 years of age, signifying the working population. The average years of higher education directly enter our final estimation as a control.

State Government Expenditure

Lastly, we control for state government expenditures using data from the U.S. Census Bureau's State Government Finances.[44] The website contains data from 1991, but full historical data is provided upon an email request. The historical file contains state government expenditure and revenue data for each state for our time period of interest, 1979 to 2008. The file contains the section "Internet data", which includes the state government total direct general expenditures (labelled "direct general expenditure"). State government direct general expenditure includes state government expenditures for education services, social services and income maintenance, transportation, public safety, environment and housing, governmental administration, interest on general debt, and other general expenditures. It excludes any expenditures classified as intergovernmental, utility, liquor stores, and employee-retirement or other insurance trust. We then deflate the government expenditure by the GDP deflator and government expenditure enters the control variables in our estimation as a log fraction of state GDP (Government Expenditure $= \log \frac{\text{Total Amount of Government Direct General Expenditure}}{\text{GDP}}$). Table D4 summarises all of our controls for the 49 states in our analysis.

State Income Growth

We use the same BEA data tool from which we acquired state GDP data to gather state income growth, which enters our consumption regression and certain robustness checks. Specifically, under regional data, the series "Annual State Personal Income and Employment" (Table SA1) contains personal income per capita for each state from 1979 to 2008, which we deflate to 2009 using the GDP deflator. This then enters our tables as the log change, representing the state income growth rate ($\text{Income Growth}_{s,t-1} = \log \text{Income}_{s,t-1} - \log \text{Income}_{s,t-2}$).

[44] See https://www.census.gov/govs/state/.

B.4 Instruments

Political Climate

Our alternative instrument set includes measures on the political climate of each state. For this purpose, we use election results for sitting legislators in the state house and senate, and for state governor. We use the Inter-university Consortium for Political and Social Research (ICPSR) database of state legislative election results (Klarner *et al.*, 2013), and the Congressional Quarterly Press Voting and Elections Collection data on gubernatorial elections (CQ Press, 2014). The legislative election data contains the length of term for each elected official (variable $V15$) and legislator party (variable $V21$). The CQ gubernatorial elections data similarly contains the variables *winner_party* and *state_governor_term*. Therefore, we are able to construct a time series database of the party in each legislative and gubernatorial seat for each year.[45] We then create three political climate variables that document the democratic party presence in the legislative and executive branches of each state's government. Our first two instruments measure the strength of the democratic party's legislative control using the share of legislative seats occupied by democrats in the state upper house (State Senate) and the state lower house (State House). The third is a dummy variable that indicates whether there is a democratic governor (Governor). Both datasets span our desired timeline of 1979 to 2008.

Demographic Instruments

The remainder of our alternative instruments are three demographic variables that can affect state policies on tax credit and welfare, including the fraction of the elderly population, the fraction of the population between ages 5 and 17, and the fraction of single mother household. We use population estimates from the U.S. Census Bureau to collect the population of individuals 65 years or older in each state (U.S. Census, 2013). We collect data from CPS on the number of single mother households and the fraction of the population between ages 5 and 17 (IPUMS-CPS). To identify single mothers we use the CPS variable for marital status (*marst*) while using the household relationship variable (*relate*) to calculate the number of below age 18 children in the household. We then consider a household to be a single mother household if the head of the household is an unmarried female with at least one dependent child under the age of 18. Using these data sources, we calculate our three demographic instruments: fraction of state population age 65 and older (Elderly), fraction of state population between ages 5 and 17 (Age 5 to 17 population), and fraction of state households that are single mother households (Elderly).

C First Stage

Tables D5 and D6 report the relevance of our main set of exogenous instruments with respect to the contraction factors (see the discussion in Section 2.2). The first two columns report the relevance of our instruments

[45] Nebraska's state legislature is unicameral and does not specify party affiliations for candidates during elections. As a result, the Nebraska state legislative data is missing.

in the first difference equation and the next two columns report the relevance of our instruments in the level equation.

Columns (1) of Table D5 shows that positive shocks to personal income tax rates are positively associated with the contraction factor $C(10)$. This is because higher tax rates lead to a decrease in post-tax income inequality relative to pre-tax income inequality. We also note from Column (1) that negative shocks to corporate income tax rates are positively correlated with $C(10)$. This may be because less corporate taxes lead to less funds for possible tax credits. Column (2) shows that shocks to $C(90)$ also correlate with shocks to personal and corporate tax rates with different sensitivities. In addition, we note that the effect of higher personal income tax rates on $C(90)$ decreases with higher initial (1979) inequality between median and above median households. This suggests that states with higher initial inequality reduce inequality less over time through above median income tax policy, i.e. $C(90)$ in our case.

Table D6 reports the first stage of our alternative set of instruments, which are political and demographic. Column (3) shows that when the state house is in control of Democrats, then tax policy attempts to bring median and median household incomes closer. This is also true when the state's governor is a Democrat. In terms of demographic instruments, we note that states with a larger elderly population and states with less single mothers also have a higher $C(10)$. Column (4) shows that when the state senate, which is the more stable legislative chamber, is under the control of Democrats, then tax policy is used more to reduce the income inequality between above median households and median households. However, *ceteris paribus* Democrat governors do not lead to higher taxes on the above median households relative to median households.

D Additional Tables

The following tables contain further statistics such as data availability, averages by states for instruments and controls, cross correlation tables, and first stage regressions.

Table D1: Sample Selection

This table shows the number of state-year observations based on our sample selection criteria from TAXSIM. We exclude Alaska due to small sample size and large differences between the moments of TAXSIM data and IRS full SOI sample. For each of the remaining state, we restrict our analysis to the years that the state has at least 500 tax return observations in the TAXSIM data. The table also shows the minimum, maximum, and average observations for each states in a year. Data is not available for any state in 1982.

State	Years of Data	Years Available	Annual Observations in State Sample		
			Minimum	Maximum	Mean
Alabama	29	79-81, 83-08	2194	4590	3336.069
Arizona	29	79-81, 83-08	875	3382	1665.793
Arkansas	25	79-81, 83, 85, 87, 89, 91-08	511	2096	790.24
California	29	79-81, 83-08	10291	20758	15513.14
Colorado	29	79-81, 83-08	914	3261	2130.172
Connecticut	29	79-81, 83-08	1123	2991	2003.724
Delaware	4	79-81, 98	739	1655	1167.5
Florida	29	79-81, 83-08	4238	9138	6746.414
Georgia	29	79-81, 83-08	1214	4197	2741.793
Hawaii	8	79-81, 83, 85, 92, 98, 00	620	3185	1498.875
Idaho	5	79-81, 96-97	962	2981	1763
Illinois	29	79-81, 83-08	3680	8382	5641.483
Indiana	29	79-81, 83-08	1142	3241	2037.483
Iowa	28	79-81, 83-85, 87-08	629	3235	1159.893
Kansas	29	79-81, 83-08	587	2288	1040.276
Kentucky	28	79-81, 83-85, 87-08	727	2744	1417.786
Louisiana	29	79-81, 83-08	823	2467	1413.483
Maine	6	79-81, 83, 85, 98	565	3009	1507.667
Maryland	29	79-81, 83-08	1172	3356	2426.103
Massachusetts	29	79-81, 83-08	1965	4248	3066
Michigan	29	79-81, 83-08	2481	5894	4469.414
Minnesota	29	79-81, 83-08	1236	3470	2086.655
Mississippi	22	79-81, 83-85, 87, 89, 91, 95-01, 03-08	501	2293	943.091
Missouri	29	79-81, 83-08	1115	3050	1833.034
Montana	4	79-81, 00	942	2783	1902.25
Nebraska	17	79-81, 87, 93, 96-99, 01-08	503	2113	833.353
Nevada	21	79-81, 86-91, 96, 98-08	642	2943	1524.095
New Hampshire	14	79-81, 92, 94-95, 97, 00, 03-08	506	2462	996.714
New Jersey	29	79-81, 83-08	2806	6462	4462.483
New Mexico	8	79-81, 86-90	1134	3339	1725.375
New York	29	79-81, 83-08	6121	13237	8978
North Carolina	29	79-81, 83-08	1480	3169	2508.069
North Dakota	3	79-81	744	2033	1508
Ohio	29	79-81, 83-08	2480	6903	4626.655
Oklahoma	29	79-81, 83-08	651	2868	1361.379
Oregon	28	79-81, 83-86, 87-08	643	2604	1241.429
Pennsylvania	29	79-81, 83-08	3265	7218	4862
Rhode Island	4	79-81, 91	831	2062	1401
South Carolina	29	79-81, 83-08	730	2028	1165.793
South Dakota	3	79-81	729	2304	1647.333
Tennessee	29	79-81, 83-08	1247	2810	1980.793
Texas	29	79-81, 83-08	4650	11515	8011.793
Utah	13	79-81, 90, 98, 01-08	522	4162	1242.923
Vermont	3	79-81	1030	1711	1453.667
Virginia	29	79-81, 83-08	1424	4033	2818.069
Washington	29	79-81, 83-08	1299	3096	2195.69
West Virginia	17	79-81, 83, 85, 87-90, 01-08	538	1888	930.353
Wisconsin	29	79-81, 83-08	776	2555	1503.207
Wyoming	3	79-81	706	2672	1930.333
Total	1076		501	20758	3063.959

Table D2: Average State GDP Growth Rates and Contraction Factors

We pool the state-level GDP, GDP growth rate, both contraction factors, and the annual change in average marginal tax rate across 49 states from 1979 to 2008 (GDP growth rate is from 1980 to 2009). This table shows the pooled averages for each of the economic growth variables, contraction factors, and change in average marginal tax rate.

State	Real Chained GDP per Capita (2009 $)	Real Chained GDP Growth Rate (%)	Contraction Factor (90th Percentile)	Contraction Factor (10th Percentile)	Change in Average Marginal Tax Rate
Alabama	29,999	1.53	0.1889	0.0711	0.01979
Arizona	33,583	1.27	0.1604	0.0816	0.00231
Arkansas	29,658	1.86	0.1578	0.066	-0.00537
California	42,569	1.54	0.1666	0.0932	0.00803
Colorado	42,028	1.59	0.1736	0.0991	0.00522
Connecticut	52,587	2.18	0.1921	0.1116	0.00693
Delaware	44,958	1.54	0.2221	0.1262	0.01699
Florida	35,195	1.23	0.1741	0.0846	0.00977
Georgia	37,799	1.61	0.1657	0.0841	0.00264
Hawaii	40,828	0.16	0.1776	0.1129	0.01117
Idaho	23,762	-0.57	0.1971	0.082	0.024
Illinois	42,493	1.5	0.182	0.0954	0.00595
Indiana	35,171	1.39	0.1704	0.0943	0.00388
Iowa	35,086	1.99	0.1571	0.0914	0.00012
Kansas	36,275	1.33	0.1723	0.0889	-0.00049
Kentucky	32,164	1.29	0.1614	0.0806	0.00501
Louisiana	39,354	1.26	0.1673	0.0687	0.00332
Maine	26,264	2.68	0.1796	0.1014	0.01551
Maryland	42,580	1.7	0.1685	0.1041	0.00404
Massachusetts	46,276	2.26	0.1746	0.1125	0.00431
Michigan	37,077	0.32	0.1769	0.0938	0.00448
Minnesota	40,695	1.82	0.1568	0.1004	0.00309
Mississippi	26,366	0.97	0.1506	0.0572	0.00377
Missouri	36,431	1.32	0.169	0.0843	0.00156
Montana	28,603	-0.13	0.2046	0.1047	0.0211
Nebraska	40,144	1.91	0.1581	0.0779	0.00009
Nevada	45,699	-0.29	0.1845	0.0988	0.01348
New Hampshire	38,494	1.55	0.1742	0.1077	0.01151
New Jersey	47,774	1.74	0.1877	0.108	0.00925
New Mexico	25,066	0.99	0.1849	0.083	0.00069
New York	47,619	1.77	0.1706	0.0966	0.00615
North Carolina	36,974	1.63	0.1554	0.0806	0.0026
North Dakota	25,777	1.22	0.2089	0.1041	0.00206
Ohio	36,318	1.3	0.1669	0.098	0.00748
Oklahoma	31,990	1.62	0.1599	0.0806	0.00453
Oregon	32,359	2.37	0.1539	0.096	0.00129
Pennsylvania	37,053	1.59	0.1731	0.0941	0.00497
Rhode Island	28,041	0.78	0.1889	0.1252	0.00461
South Carolina	31,640	1.45	0.145	0.0759	0.00049
South Dakota	20,096	-0.64	0.1949	0.0958	0.0017
Tennessee	34,294	1.54	0.1686	0.0787	0.0046
Texas	39,233	1.46	0.1836	0.0782	0.00632
Utah	36,708	0.53	0.1346	0.0761	0.00044
Vermont	24,457	2.6	0.1936	0.1061	0.00631
Virginia	41,815	1.79	0.177	0.098	0.02026
Washington	44,809	1.22	0.1775	0.1048	0.00298
West Virginia	27,915	1.12	0.1724	0.0824	0.00919
Wisconsin	36,520	1.56	0.1507	0.0971	-0.00324
Wyoming	38,914	-2.02	0.2214	0.1337	0.00872
Total	37,704	1.46	0.1696	0.0904	0.00526

Table D3: Contraction Factors and Inequality Cross-correlation

This table shows the cross-correlations between our contraction factors, income inequality ratios, and the Gini coefficient. Panel A presents the standard correlations, while Panel B uses demeaned variables to show correlations with state fixed effects.

Panel A: Standard Cross-Correlation

Variables	$C(90)$	$C(10)$	$\frac{\text{Income(90)}}{\text{Income(50)}}$	$\frac{\text{Income(50)}}{\text{Income(10)}}$	Gini
$C(90)$	1.000				
$C(10)$	0.602	1.000			
$\frac{\text{Income(90)}}{\text{Income(50)}}$	-0.098	-0.523	1.000		
$\frac{\text{Income(50)}}{\text{Income(10)}}$	-0.036	-0.048	-0.065	1.000	
Gini	-0.111	-0.431	0.758	0.153	1.000

Panel B: State Fixed Effects Cross-Correlation

Variables	$C(90)$	$C(10)$	$\frac{\text{Income(90)}}{\text{Income(50)}}$	$\frac{\text{Income(50)}}{\text{Income(10)}}$	Gini
$C(90)$	1.000				
$C(10)$	0.673	1.000			
$\frac{\text{Income(90)}}{\text{Income(50)}}$	-0.264	-0.568	1.000		
$\frac{\text{Income(50)}}{\text{Income(10)}}$	-0.075	-0.183	0.024	1.000	
Gini	-0.377	-0.591	0.728	0.288	1.000

Table D4: Averages for Control Variables

We pool our income ratios between 50th and 10th, and 90th and 50th percentiles, average years of higher education beyond 12th grade, and log state government direct general expenditures as a ratio of GDP across 49 states from 1979 to 2008. This table shows the pooled averages for each of our controls.

State	Income Ratio: 50th to 10th Percentile	Income Ratio: 90th to 50th Percentile	Years of Higher Education	Government Expenditure ($\log \frac{\text{Direct General Exp.}}{\text{GDP}}$)
Alabama	5.519	4.002	1.115	-2.545
Arizona	5.018	3.200	1.466	-2.891
Arkansas	5.485	3.111	1.029	-2.525
California	5.470	3.343	1.608	-3.017
Colorado	6.288	3.058	1.832	-3.056
Connecticut	6.712	3.257	1.765	-2.770
Delaware	5.318	3.133	1.329	-2.761
Florida	4.910	3.383	1.363	-3.016
Georgia	5.400	3.280	1.338	-2.920
Hawaii	5.793	3.317	1.456	-2.266
Idaho	5.468	3.807	1.236	-2.610
Illinois	6.589	3.190	1.498	-2.976
Indiana	6.703	2.893	1.111	-2.867
Iowa	6.302	2.895	1.353	-2.651
Kansas	6.222	3.199	1.590	-2.839
Kentucky	5.581	3.144	1.129	-2.481
Louisiana	5.615	3.407	1.175	-2.692
Maine	5.106	2.695	1.072	-2.567
Maryland	6.299	3.070	1.718	-2.801
Massachusetts	6.297	3.072	1.809	-2.631
Michigan	6.854	3.175	1.313	-2.767
Minnesota	6.599	3.006	1.639	-2.766
Mississippi	5.257	3.366	1.187	-2.442
Missouri	5.831	3.176	1.359	-2.935
Montana	5.443	4.254	1.289	-2.612
Nebraska	6.509	3.102	1.484	-2.762
Nevada	4.500	3.547	1.276	-3.198
New Hampshire	7.052	2.940	1.747	-2.676
New Jersey	6.538	3.213	1.626	-2.914
New Mexico	6.357	3.332	1.269	-2.456
New York	5.806	3.271	1.540	-2.852
North Carolina	5.366	3.177	1.291	-2.886
North Dakota	7.062	2.763	1.123	-2.485
Ohio	6.130	2.952	1.266	-2.848
Oklahoma	5.610	3.184	1.309	-2.672
Oregon	5.768	2.954	1.552	-2.500
Pennsylvania	6.613	3.092	1.277	-2.769
Rhode Island	5.202	2.729	1.220	-2.410
South Carolina	5.062	3.135	1.180	-2.540
South Dakota	6.720	2.898	0.938	-2.363
Tennessee	5.806	3.124	1.125	-2.810
Texas	5.798	3.421	1.369	-3.077
Utah	5.607	2.916	1.666	-2.535
Vermont	5.476	3.043	1.392	-2.234
Virginia	6.073	3.145	1.602	-2.928
Washington	6.043	2.781	1.661	-2.806
West Virginia	5.772	3.106	0.865	-2.297
Wisconsin	6.219	2.983	1.379	-2.780
Wyoming	6.632	2.436	1.304	-2.929
Total	5.923	3.171	1.404	-2.773

Table D5: The Effects of Tax Shock Instruments on Log Contraction Factors

This table shows results on the relationship between our log contraction factors and exogenous instruments. Columns (1) and (2) show the first difference estimation, which is one of the first stages of system GMM, using our tax shock exogenous instruments, where Column (1) has the changes in below median contraction factor as dependent variable and Column (2) has the changes in above median contraction factor as dependent variable. Columns (3) and (4) show the levels equation, the other first stage of system GMM, using our political and demographic exogenous instruments, where Column (3) has the below median contraction factor as dependent variable and Column (4) has the above median contraction factor as dependent variable. The lower portion of the table shows regressions statistics: the use of fixed effects and other covariates, R^2, F statistics, relevant first-stage p-values (Angrist-Pischke F and χ^2, and Anderson-Rubin), number of observations, and the mean of the dependent contraction factor.

First Difference Specification:
$\Delta \log C_{s,t}(i) = \Delta Z_{s,t}\gamma + \Delta\text{other controls} + \text{internal instruments} + \Delta\varepsilon_{s,t}$

Levels Specification:
$\log C_{s,t}(i) = \alpha_0 + Z_{s,t}\gamma + \Delta\text{internal instruments} + \text{other controls} + \delta_s + \eta_t + \varepsilon_{s,t}$

Z: Tax shock instruments (personal and corporate tax shocks interacted with charity and state income inequality in 1979)

	First Difference		Levels	
Model	$\Delta\log C(10)$	$\Delta\log C(90)$	$\log C(10)$	$\log C(90)$
Regressors	(1)	(2)	(3)	(4)
z_{pi}	0.049**	0.125***		
	(0.024)	(0.012)		
$\Delta z_{pi} \times \log\frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$	-0.082	0.041		
	(0.079)	(0.038)		
$\Delta z_{pi} \times \log\frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$	0.160	-0.149**		
	(0.150)	(0.073)		
$\Delta z_{pi} \times \text{Charity}_{1979}$	-2.319	2.336		
	(3.394)	(1.657)		
z_{ci}	-0.019***	-0.014***		
	(0.004)	(0.002)		
$\Delta z_{ci} \times \log\frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$	-0.015	-0.001		
	(0.014)	(0.007)		
$\Delta z_{ci} \times \log\frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$	0.037	0.019		
	(0.028)	(0.014)		
$\Delta z_{ci} \times \text{Charity}_{1979}$	0.583	-0.291		
	(0.795)	(0.388)		
$z_{pi} \times \log\frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$			-0.468**	0.020
			(0.218)	(0.100)
$z_{pi} \times \log\frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$			-0.020	-0.330*
			(0.398)	(0.182)
$z_{pi} \times \text{Charity}_{1979}$			-1.350	4.333**
			(4.519)	(2.071)
$z_{ci} \times \log\frac{\text{Income}_{1979}(50)}{\text{Income}_{1979}(10)}$			0.027	-0.012
			(0.031)	(0.014)
$z_{ci} \times \log\frac{\text{Income}_{1979}(90)}{\text{Income}_{1979}(50)}$			0.067	0.019
			(0.056)	(0.025)
$z_{ci} \times \text{Charity}_{1979}$			0.401	-0.747*
			(0.969)	(0.444)
State FE	N	N	Y	Y
Time FE	N	N	Y	Y
Internal Instruments	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
R^2	0.1504	0.3336	0.7104	0.6976
F statistic (All regressors)	9.1938	26.0021	89.2544	106.7472
p value	0.0000	0.0000	0.0000	0.0000
F statistic (External instruments only)	10.0070	31.5592	1.6431	1.3003
p value	0.0000	0.0000	0.1321	0.2542
Angrist-Pischke F (p value)	0.0000	0.0000	0.0404	0.0047
Angrist-Pischke χ^2 (p value)	0.0000	0.0000	0.0088	0.0002
Anderson-Rubin (p value)	0.0000	0.0000	0.0037	0.0037
# Observations	953	953	989	989
# Instruments	13	13	11	11
Means:				
Log Contraction Factor	-2.4478	-1.7876	-2.4393	-1.7846
Contraction Factor	0.0898	0.1690	0.0905	0.1694

Significance Levels: * 10% ** 5% *** 1%

Standard errors are clustered at the state-level.

Table D6: The Effects of Political and Demographic Instruments on Log Contraction Factors

This table shows results on the relationship between our log contraction factors and exogenous instruments. Columns (1) and (2) show the first difference estimation, which is one of the first stages of system GMM, using our tax shock exogenous instruments, where Column (1) has the changes in below median contraction factor as the dependent variable and Column (2) has the changes in above median contraction factor as dependent variable. Columns (3) and (4) show the levels equation, the other first stage of system GMM, using our political and demographic exogenous instruments, where Column (3) has the below median contraction factor as the dependent variable and Column (4) has the above median contraction factor as dependent variable. The lower portion of the table shows regression statistics: the use of fixed effects and other covariates, R^2, F statistics, relevant first-stage p-values (Angrist-Pischke F and χ^2, and Anderson-Rubin), number of observations, and the mean of the dependent contraction factor.

First Difference Specification:
$\Delta \log C_{s,t}(i) = \Delta Z'_{s,t}\gamma + \Delta\text{other controls} + \text{internal instruments} + \Delta\varepsilon_{s,t}$

Levels Specification:
$\log C_{s,t}(i) = \alpha_0 + Z'_{s,t}\gamma + \Delta\text{internal instruments} + \text{other controls} + \delta_s + \eta_t + \varepsilon_{s,t}$

Z': Political affiliation and demographic instruments (share of state legislative bodies and governorship, elderly population, age 5 to 17 population, single mother households)

	First Difference		Levels	
Model	$\Delta\log C(10)$	$\Delta\log C(90)$	$\log C(10)$	$\log C(90)$
Regressors	(1)	(2)	(3)	(4)
Δ State Senate	-0.018	0.033		
	(0.098)	(0.052)		
Δ State House	-0.099	-0.001		
	(0.112)	(0.059)		
Δ Governor	0.016	-0.002		
	(0.013)	(0.007)		
Δ Elderly	3.398	-0.112		
	(3.693)	(1.936)		
Δ Age 5 to 17 population	0.193	-0.155		
	(0.387)	(0.203)		
Δ Single Mother	-0.702**	-0.008		
	(0.319)	(0.167)		
State Senate			-0.010	0.081***
			(0.059)	(0.028)
State House			0.295***	0.017
			(0.067)	(0.031)
Governor			0.017**	-0.010***
			(0.008)	(0.004)
Elderly			3.193***	0.653
			(0.986)	(0.462)
Age 5 to 17 population			0.140	0.245
			(0.342)	(0.160)
Single Mother			-0.851***	0.058
			(0.320)	(0.150)
State FE	N	N	Y	Y
Time FE	N	N	Y	Y
Internal Instruments	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
R^2	0.0992	0.1673	0.6935	0.6830
F statistic (All regressors)	6.6007	12.0448	99.9166	109.9987
p value	0.0000	0.0000	0.0000	0.0000
F statistic (External instruments only)	1.3656	0.1969	10.2546	5.0297
p value	0.2255	0.9777	0.0000	0.0000
Angrist-Pischke F (p value)	0.0167	0.3884	0.0001	0.0187
Angrist-Pischke χ^2 (p value)	0.0041	0.3360	0.0000	0.0024
Anderson-Rubin (p value)	0.0000	0.0000	0.0000	0.0000
# Observations	975	975	1011	1011
# Instruments	11	11	11	11
Means:				
Log Contraction Factor	-2.4606	-1.7930	-2.4518	-1.7899
Contraction Factor	0.0888	0.1681	0.0896	0.1686

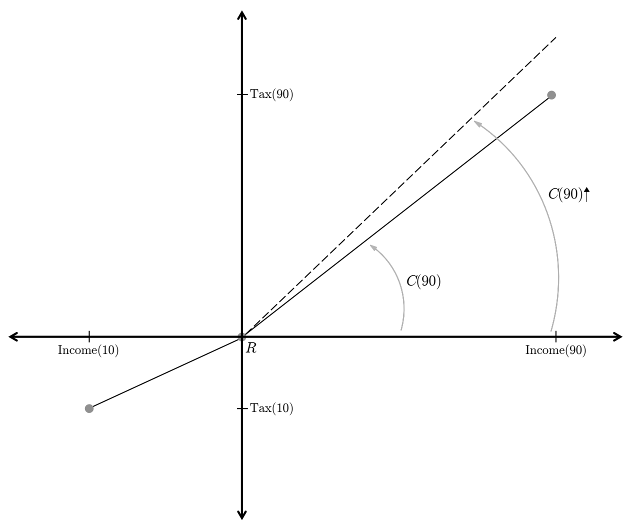
Significance Levels: * 10% ** 5% *** 1%

Standard errors are clustered at the state-level.

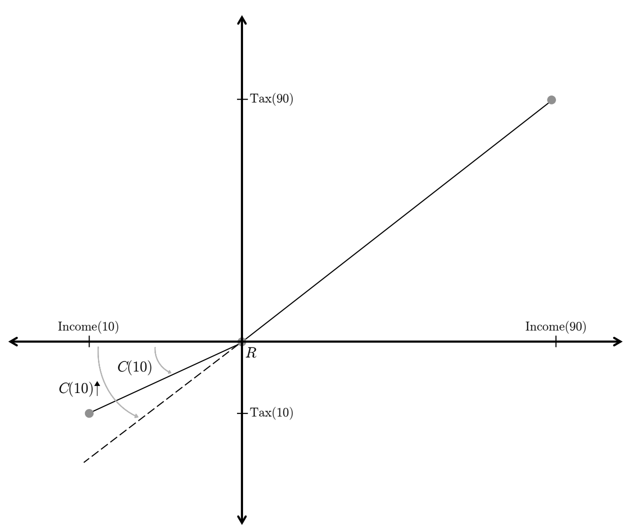
E Additional Figures

Figure E1: Graphical Interpretation of Contraction Factors

This figure illustrates the calculation and change in the contraction factors in relation to the median household (reference point $R = (Income(50), Tax(50))$). The graph plots the income distribution and taxes paid at the 10th and 90th percentile. In subfigure (a), the slope of the solid line from R to $(Income(90), Tax(90))$ represents the contraction factor between the 90th percentile households and the median households, $C(90)$. As the tax rate at the 90th percentile increases, while the median taxation is held fixed, the dotted line illustrates an increase in $C(90)$. In subfigure (b), the slope of the solid line from R to $(Income(10), Tax(10))$ represents the contraction factor between the 10th percentile households and the median households, $C(10)$. As the tax rate at the 10th percentile decreases, while the median taxation is held fixed, the dotted line illustrates an increase in $C(10)$. An increase in the contraction factor between the ith household and the median household, $C(i)$, signifies a further reduction in income inequality between the ith percentile and the reference median household due to taxation.



(a) Contraction factor $C(90)$

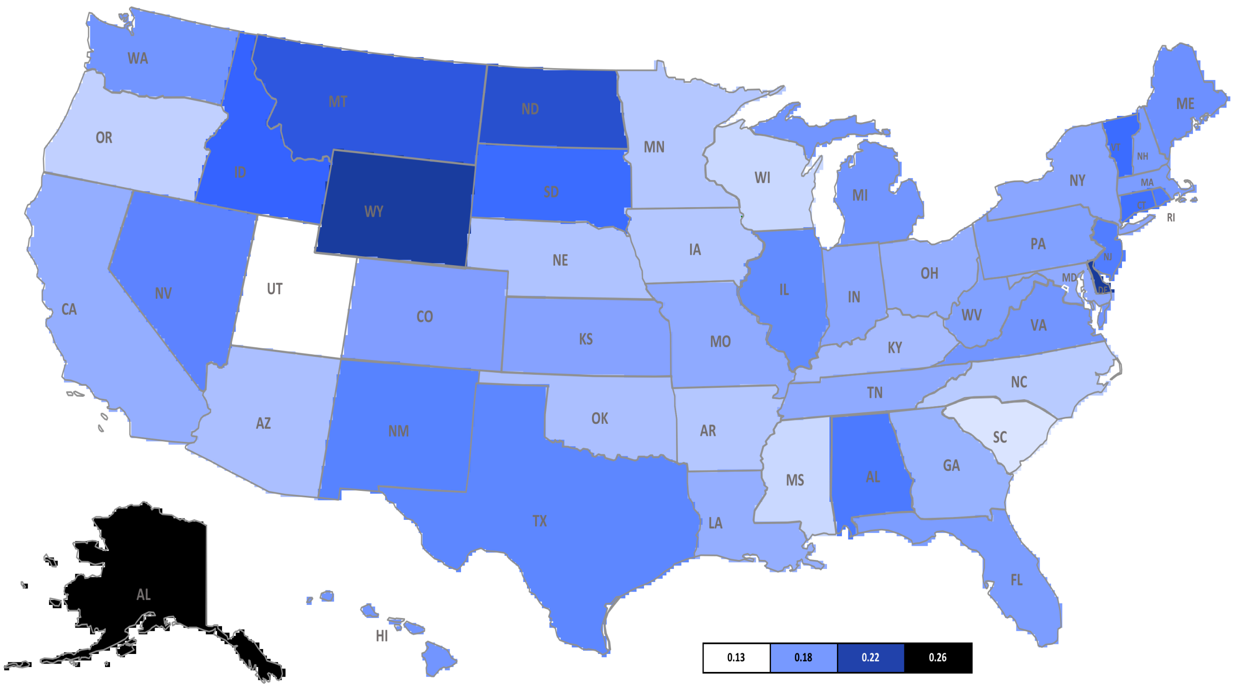


(b) Contraction factor $C(10)$

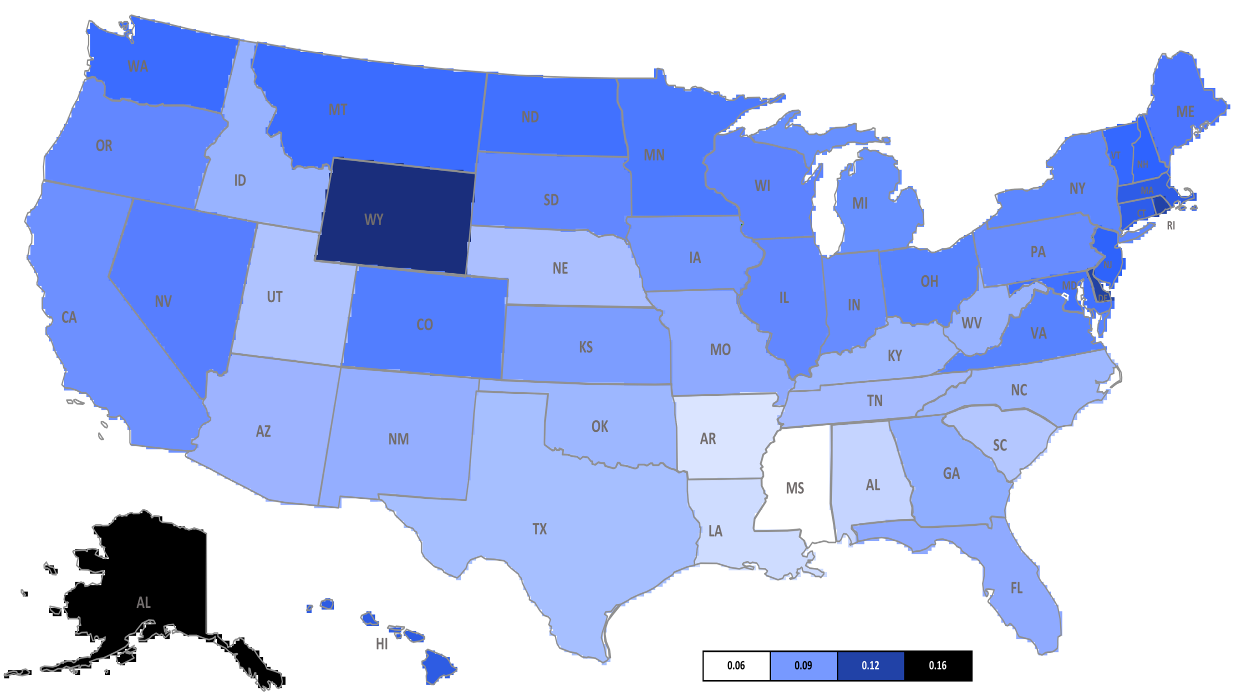
The contraction factors are in relation to reference point $R = (Income(50), Tax(50))$

Figure E2: Contraction Factors across States: Average

This figure illustrates the state averages for both contraction factors, $C(90)$ and $C(10)$. The darker states represent a higher average contraction factor.



(a) Contraction factor $C(90)$



(b) Contraction factor $C(10)$

Figure E3: Average Contraction Factors and Narrative Shocks Measures

This figure shows the average contraction factors that cover all states from 1979 to 2008. The narrative shocks measures are shocks to personal income liability given by Mertens and Ravn (2013).