Responses to Taxes & Transfers Part 1 – Labor Supply

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GOALS OF THIS LECTURE

1) Cover empirical studies of labor supply responses to taxation going historically from earlier to more recent papers. Contributes to our highly important “internal paper repertoire” (IPR).

2) Understand key methodologies such as diff-in-diff; non-linear budget sets and “bunching at the kinks,” which are useful for a wide range of empirical work.

3) Critically discuss papers’ methodologies and results so as to practice our research skills.
MOTIVATION

1) Labor supply responses to taxation are of fundamental importance for income tax policy [efficiency costs and optimal tax formulas]

2) Labor supply responses along many dimensions:
   
   (a) Intensive: hours of work on the job, intensity of work, how much skill to build

   (b) Extensive: whether to work or not [e.g., retirement and migration decisions]; occupational choice [including level of education].

3) Reported earnings for tax purposes can also vary due to (a) tax avoidance [legal tax minimization], (b) tax evasion [illegal under-reporting]

4) Different responses in short-run and long-run: long-run response most important for policy but hardest to estimate
Data on hours or work, wage rates, non-labor income started becoming available in the 1960s when first micro surveys and computers appeared:

Simple OLS regression:

\[ l_i = \alpha + \beta w_i + \gamma y_i + X_i \delta + \epsilon_i \]

\( w_i \) is the net-of-tax wage rate

\( y_i \) measures non-labor income [including spousal earnings for couples]

\( X_i \) are demographic controls [age, experience, education, etc.]

\( \beta \) measures uncompensated wage effects, and \( \gamma \) income effects [can be converted to \( \varepsilon^u, \eta \)]
BASIC CROSS SECTION RESULTS

   
a) Small effects $\varepsilon^u = 0$, $\eta = -0.1$, $\varepsilon^c = 0.1$ with some variation across estimates (sometimes $\varepsilon^c < 0$).

2. Female workers [secondary earners when married] (Killingsworth and Heckman, 1986):

   Much larger elasticities on average, with larger variations across studies. Elasticities go from zero to over one. Average around 0.5. Significant income effects as well

   Female labor supply elasticities have declined overtime as women become more attached to labor market (Blau-Kahn JOLE’07)
KEY ISSUE: \( w \) CORRELATED WITH TASTES FOR WORK

\[ l_i = \alpha + \beta w_i + \gamma y_i + \epsilon_i \]

Identification is based on cross-sectional variation in \( w_i \): comparing hours of work of highly skilled individuals (high \( w_i \)) to hours of work of low skilled individuals (low \( w_i \))

If highly skilled workers have more taste for work (independent of the wage effect), then \( \epsilon_i \) is positively correlated with \( w_i \) leading to an upward bias in OLS

Plausible scenario: hard workers acquire better education and hence have higher wages

Controlling for \( X_i \) can help but can never be sure that we have controlled for all the factors correlated with \( w_i \) and tastes for work: **Omitted variable bias**

\[ \Rightarrow \] Tax changes provide more compelling identification
NEGATIVE INCOME TAX (NIT) EXPERIMENTS

1) Best way to resolve identification problems: exogenously change taxes/transfers with a randomized experiment

2) NIT experiment conducted in 1960s/70s in Denver, Seattle, and other cities

3) First major social experiment in U.S. designed to test proposed transfer policy reform

4) Provided lump-sum welfare grants $G$ combined with a steep phaseout rate $\tau$ (50%-80%) [based on family earnings]


6) Several groups, with randomization within each; approx. $N = 75$ households in each group
Disposable income
\[ c = z - T(z) \]
Table 1
Parameters of the 11 Negative Income Tax Programs

<table>
<thead>
<tr>
<th>Program Number</th>
<th>G ($)</th>
<th>$\tau$</th>
<th>Declining Tax Rate</th>
<th>Break-even Income ($)</th>
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<td>1</td>
<td>3,800</td>
<td>0.5</td>
<td>No</td>
<td>7,600</td>
</tr>
<tr>
<td>2</td>
<td>3,800</td>
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<td>No</td>
<td>5,429</td>
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<tr>
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<tr>
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<tr>
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<td>5,600</td>
<td>0.8</td>
<td>Yes</td>
<td>10,360</td>
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</table>

Source: Ashenfelter and Plant (1990), p. 403
NIT EXPERIMENTS: FINDINGS

See Ashenfelter and Plant JHR’ 90 for non-parametric evidence. More parametric evidence in earlier work. Key results:

1) Significant labor supply response but small overall

2) Implied earnings elasticity for males around 0.1

3) Implied earnings elasticity for women around 0.5

4) Academic literature not careful to decompose response along intensive and extensive margin

5) Response of women is concentrated along the extensive margin (can only be seen in official govt. report)

6) Earnings of treated women who were working before the experiment did not change much
TAX ISSUE: NON-LINEAR BUDGET SETS

Actual tax system is not linear but piece-wise linear with varying marginal tax rate $\tau$ due to (a) means-tested transfer programs, (b) progressive individual income tax

Same theory applies when considering the linearized tax system $c = wl + y$ with $w = w^P(1 - T')$ and $y$ defined as virtual income (intercept of budget with x-axis when setting $l = 0$)

Main complications:

(a) $w$ [and $y$] become endogenous to choice of $l$

(b) FOC may not hold if individual bunches at a kink

(c) FOC may not characterize the optimum choice
Non-Linear Budget Set Estimation: Virtual Incomes

Source: Hausman (Hbk 1985)
TAX ISSUE: NON-LINEAR BUDGET SETS

Non-linear budget set creates two econometric problems:

1) Model mis-specification: OLS regression no longer recovers structural elasticity parameter of interest

2) Econometric bias: $\tau_i = T'(w_i l_i)$ and $y_i$ depends on income $w_i l_i$ and hence on $l_i$

Tastes for work are positively correlated with $\tau_i$ (due to progressive tax system) $\rightarrow$ downward bias in OLS regression of hours worked on net-of-tax rates
OLD NON-LINEAR BUDGET SET METHOD

Issue addressed by non linear budget set studies pioneered by Hausman in late 1970s (Hausman, 1985 PE handbook chapter)

Method uses a structural model of labor supply to derive and estimate labor supply function fully consistent with theory

Key point: the method still uses the standard cross-sectional variation in pre-tax wages \( w^p \) for identification. Taxes are seen as a problem to deal with rather than an opportunity for identification.

New literature identifying labor supply elasticities using tax changes has a totally different perspective: taxes are seen as an opportunity to identify labor supply
FROM TRUE EXPERIMENTS TO “NATURAL EXPERIMENTS”

True experiments are costly to implement and hence rare.

However, real economic world (nature) provides variation that can be exploited to estimate behavioral responses ⇒ “Natural Experiments”

Natural experiments sometimes come very close to true experiments: Imbens, Rubin, Sacerdote AER ’01 did a survey of lottery winners and non-winners matched to Social Security administrative data (for those who agreed to release it) to estimate income effects.

Lottery generates random assignment conditional on playing.

Find significant but relatively small income effects: \( \eta = w \partial l / \partial y \) between -0.05 and -0.10.

Identification threat: differential response-rate among groups.

Caveats: generalizability/representativeness? Are lottery wins similar to other income shocks?
FIGURE 2. PROPORTION WITH POSITIVE EARNINGS FOR NONWINNERS, WINNERS, AND BIG WINNERS

Note: Solid line = nonwinners; dashed line = winners; dotted line = big winners.

On average the individuals in our basic sample won yearly prizes of $26,000 (averaged over the $55,000 for winners and zero for nonwinners). Typically they won 10 years prior to completing our survey in 1996, implying they are on average halfway through their 20 years of lottery payments when they responded in 1996. We asked all individuals how many tickets they bought in a typical week in the year they won the lottery. As expected, the number of tickets bought is considerably higher for winners than for nonwinners. On average, the individuals in our basic sample are 50 years old at the time of winning, which, for the average person was in 1986; 35 percent of the sample was over 55 and 15 percent was over 65 years old at the time of winning; 63 percent of the sample was male. The average number of years of schooling, calculated as years of high school plus years of college plus 8, is equal to 13.7; 64 percent claimed at least one year of college.

We observe, for each individual in the basic sample, Social Security earnings for six years preceding the time of winning the lottery, for the year they won (year zero), and for six years following winning. Average earnings, in terms of 1986 dollars, rise over the pre-winning period from $13,930 to $16,330, and then decline back to $13,290 over the post-winning period. For those with positive Social Security earnings, average earnings rise over the entire 13-year period from $20,180 to $24,300. Participation rates, as measured by positive Social Security earnings, gradually decline over the 13 years, starting at around 70 percent before going down to 56 percent. Figures 1 and 2 present graphs for average earnings and the proportion of individuals with positive earnings for the three groups, nonwinners, winners, and big winners. One can see a modest decline in earnings and proportion of individuals with positive earnings for the full winner sample compared to the nonwinners after winning the lottery, and a sharp and much larger decline for big winners at the time of winning. A simple difference-in-differences type estimate of the marginal propensity to earn out of unearned income (mpe) can be based on the ratio of the difference in the average change in earnings before and after winning the lottery for two groups and the difference in the average prize for the same two groups. For the winners, the difference in average earnings over the six post-lottery years and the six pre-lottery years is -$1,877 and for the nonwinners the average change is $448. Given a difference in average prize of $55,000 for the winner/nonwinners comparison, the estimated mpe is \((-1,877 - 448)/(55,000 - 0) = -0.042\) (SE 0.016). For the big-winners/small-winners comparison, this estimate is -0.059 (SE 0.018). In Section IV we report estimates for this quantity using more sophisticated analyses.

On average the value of all cars was $18,200. For housing the average value was $166,300, with an average mortgage of $44,200. We aggregated the responses to financial wealth into two categories. The first concerns retirement

\[ \text{Because there were some extremely large numbers (up to 200 tickets per week), we transformed this variable somewhat arbitrarily by taking the minimum of the number reported and ten. The results were not sensitive to this transformation.} \]

\[ \text{Note that this is averaged over the entire sample, with zeros included for the 7 percent of respondents who reported not owning their homes.} \]

\[ \text{Source: Imbens et al. (2001), p. 783} \]

**Figure 1. Average Earnings for Nonwinners, Winners, and Big Winners**

*Note:* Solid line = nonwinners; dashed line = winners; dotted line = big winners.
DIFFERENCE-IN-DIFFERENCE (DD) METHODOLOGY

Two groups: Treatment group (T) which faces a change [lottery winners] and control group (C) which does not [non winners]

Compare the evolution of T group (before and after change) to the evolution of the C group (before and after change)

DD identifies the treatment effect if the parallel trend assumption holds:

Absent the change, $T$ and $C$ would have evolved in parallel

DD most convincing when groups are very similar to start with

Should always test DD using data from more periods and plot the two time series to check parallel trend assumption
Cesarini et al. (2017) use Swedish population wide administrative data with more compelling setting: (1) bank accounts with random prizes (PLS), (2) monthly lottery subscription (Kombi), and (3) TV show participants (Triss)

Estimation:

\[ y_{it} = \beta_t L_{i,0} + X_{i,0}\delta_t + Z_{i,s}\gamma_t + \varepsilon_{i,t} \]

where \( X_{i,0} \) are “cell” fixed effects; \( Z_{i,s} \) are pre-lottery characteristics (for precision); and \( L_{i,0} \) is lottery prize won.

**Key results:**

1) Effects on both extensive and intensive labor supply margin, immediate, small & quite stable

2) Significant but relatively small income effects: \( \eta = w \partial l / \partial y \) around -0.10

3) Effects on spouse but not as large as on winner

⇒ Rejects the unitary model of household labor supply:

\[ \max u(c_1, c_2, l_1, l_2) \text{ st } c_1 + c_2 \leq w_1 l_1 + w_2 l_2 + R \] (where only household \( R \) matters).
A. Effect of Wealth on Annual Earnings

Our primary earnings measure is pretax labor earnings, a composite variable derived almost entirely from three sources of income: annual wage earnings, income from self-employment, and income support due to parental leave or sickness absence. Figure 1 depicts the estimated effect of wealth on our primary outcome for $t = -4, -3, \ldots, 10$ along with 95 percent confidence intervals. Consistent with the identifying assumption of conditional random assignment of lottery prizes, the point estimates in the years prior to winning are statistically indistinguishable from zero. The effect of lottery wealth is near-immediate, modest in size, and quite stable over time. The tendency for the effect to decline over time vanishes if we restrict the sample to individuals who were below age 55 at the time of winning and who therefore had at least 10 years left to age 65, the modal retirement age in Sweden (see Figure 3, panel B).

For the average winner, labor earnings in $t = 0$ include income from six months prior to and six months after the lottery draw, so the fact that the point estimate at $t = 0$ is about half the $t = 1$ estimate suggests that lottery players adjust labor supply quickly after winning the lottery.

Because we limit the sample to labor earnings measured in 1991–2010 and the sample consists of individuals who won the lottery in 1986–2010, the composition of the pooled sample in Figure 1 changes somewhat with $t$. For example, an individual who won the lottery in 1986 will not enter the data until $t = 5$. Conversely, an individual who won in, say, 2010, will exit the data at $t = 1$. In online Appendix Section 4, we show the time pattern of labor supply responses looks quite similar up until $t = 10$ when we hold the sample fixed. The data indicate larger responses after $t = 10$, but due to the smaller sample size, we rely on the model in Section IV instead of these estimates to make inferences about long-term effects of lottery wealth on labor supply.

**Figure 1. Effect of Wealth on Individual Earnings**

Notes: This figure reports estimates obtained from equation (2) estimated in the pooled lottery sample with pretax labor earnings as the dependent variable. A coefficient of 1.00 corresponds to an increase in annual earnings of 1 SEK for each 100 SEK won. Each year corresponds to a separate regression and the dashed lines show 95 percent confidence intervals.
To more carefully assess the unitary model, we exclude the Triss lottery from columns 7–10, for two reasons. First, married couples may sometimes buy Triss lottery tickets together, implying ownership of the winning ticket within the couple is unclear. By contrast, both the winning account in PLS and lottery ticket subscription in Kombi pertain to a specific individual. Using data from the Wealth Registry, we find married winners in Kombi and PLS retain a larger share of households' observable lottery wealth (78 percent and 85 percent) than married Triss winners (72 percent), suggesting within-couple ownership is indeed more clearly defined in the former two lotteries. Second, nonwinning spouses may differ systematically from winning spouses in ways that correlate with how they respond to wealth shocks. In Triss, this concern is difficult to put to a stringent test, because we do not have information about the population of lottery players who selected into the lottery, only players who appear on the TV show. In PLS and Kombi, we have information about the universe of players and the number of tickets owned. This information allows us to test if the differential response observed between winners and their spouses persists in households where both spouses participated in the lottery.

Column 7 of Table 6 shows restricting attention to the PLS and Kombi samples increases the spousal difference to $-0.964$ ($p=0.015$), in line with the relatively

32 The Triss data contain information about shared ownership of lottery tickets, but the data rarely indicate shared ownership between married spouses, probably because "contracts" regarding ownership are less explicit between spouses, and because wealth is split equally in the event of a divorce. Consequently, in some cases, married couples are likely to have bought a winning ticket together, but only one of the spouses appears on the show.

33 Online Appendix Figure A5 and Table A5 show the complete results for how lottery wealth is allocated between spouses. Because the Swedish Wealth Registry only existed in 1999–2007, we observe wealth for very few winners in PLS and therefore use capital income as a proxy for wealth in this case. We exclude Triss-Monthly winners because inferring how the prize money is allocated within couples when it is paid out over a long time is difficult.

**Figure 5. Effect of Wealth on Earnings of Married Winners and Spouses**

*Notes:* This figure reports estimates obtained from estimating equation (2) separately for married winners, their spouses, and married households. The dependent variable is pretax labor earnings. Each year corresponds to a separate regression.
1) Identify elasticities from 1980-2000 using grouping instrument

a) Define cells (year $\times$ age $\times$ education) and compute mean wages

b) Instrument for actual wage with mean wage in cell

2) Identify purely from group-level variation, which is less contaminated by individual endogenous choice

3) Results: (a) total hours elasticity for married women (including intensive + extensive margin) shrank from 0.4 in 1980 to 0.2 in early 2000s, (b) effect of husband earnings ↓ overtime

4) Interpretation: elasticities shrink as women become more attached to the labor force
SUMMARY OF STATIC LABOR SUPPLY LITERATURE

1) Small elasticities for prime-age males

Probably institutional restrictions, need for at least one income, etc. prevent a short-run response

2) Larger responses for workers who are less attached to labor force: Married women, low income earners, retirees

3) Responses driven primarily by extensive margin

a) Extensive margin (participation) elasticity around 0.2-0.5

b) Intensive margin (hours) elasticity smaller
RESPONSES TO LOW-INCOME TRANSFER PROGRAMS

1) Particular interest in treatment of low incomes in a progressive tax system: are they responsive to incentives?

2) Complicated set of transfer programs in US
   a) In-kind: food stamps, Medicaid, public housing, job training, education subsidies
   b) Cash: TANF, EITC, SSI

3) See Gruber undergrad textbook for details on institutions
1996 US WELFARE REFORM

1) Reform modified AFDC cash welfare program to provide more incentives to work (renamed TANF)
   a) Requiring recipients to go to job training or work
   b) Limiting the duration for which families able to receive welfare
   c) Reducing phase-out rate of benefits


4) EITC also expanded during this period: general shift from welfare to “workfare”

Did welfare reform and EITC increase labor supply?
Figure 1. Number of Families Receiving AFDC/TANF Cash Assistance, 1959-2013

Source: Falk (2016)

(Families in millions)

Source: Congressional Research Service (CRS), based on data from the U.S. Department of Health and Human Services (HHS).

Notes: Shaded areas represent recessionary periods. Families receiving TANF cash assistance since October 1, 1999, include families receiving cash assistance from separate state programs (SSPs) with expenditures countable toward the TANF maintenance of effort requirement (MOE).
The landscape providing assistance to poor families with children has changed substantially.
THEORETICAL BEHAVIORAL RESPONSES TO AN EITC

**Extensive margin:** positive effect on Labor Force Participation as EITC makes work more attractive

**Intensive margin:** earnings conditional on working, mixed effects

1) Phase in: (a) Substitution effect: work more due to wage subsidy, (b) Income effect: work less ⇒ Net effect: ambiguous; probably work more

2) Plateau: Pure income effect (no change in net wage) ⇒ Net effect: work less

3) Phase out: (a) Substitution effect: work less, (b) Income effect: also work less ⇒ Net effect: work less

Should expect bunching at the EITC kink points
RANDOMIZED WELFARE EXPERIMENT: 
SSP WELFARE DEMONSTRATION IN CANADA

Canadian Self Sufficiency Project (SSP): randomized experiment that gave welfare recipients an earnings subsidy for 36 months in 1990s (but need to start working by month 12 to get it)

3 year temporary participation tax rate cut from average rate of 74.3% to 16.7% [get to keep 83 cents for each $ earned instead of 26 cents]

Card and Hyslop (EMA 2005) provide classic analysis. Two results:

1) Strong effect on employment rate during experiment (peaks at 14 points)

2) Effect quickly vanishes when the subsidy stops after 36 months (entirely gone by month 52)
and control groups. Unfortunately, these data have some critical limitations relative to the administratively based Income Assistance data. Most importantly, they are only available for 52 months after random assignment. Since some program group members were still receiving subsidy payments as late as month 52, this time window is too short to assess the long-run effects of the program. Indeed, looking at Figure 1a, there is still an impact on IA participation in month 52 that does not fully dissipate until month 69. Second, because of nonresponses and refusals, labor market information is only available for 85% of the experimental sample (4,757 people). Third, there appear to be relatively large recall errors and seam biases in the earnings and wage data.

Nevertheless, the labor market outcomes provide a valuable complement to the administratively based welfare participation data.

Figure 3 shows the average monthly employment rates of the program and control groups, along with the associated experimental impacts. After random assignment the employment rate of the control group shows a steady

![Figure 3. Monthly employment rates.](source: Card and Hyslop, 2005, p. 1734)

Source: Card and Hyslop, 2005, p. 1734
See Kleven (2020) provides comprehensive ex-post re-analysis using women aged 20-50 and CPS data

1) EITC started small in the 1970s but was expanded in 1986-88, 1994-96, 2008-09: today, largest means-tested cash transfer program [$70bn in 2016, 30m families recipients]

2) Eligibility: families with kids and low earnings.

3) Refundable Tax credit: administered as annual tax refund received in Feb-April, year $t + 1$ (for earnings in year $t$)

4) EITC has flat pyramid structure with phase-in (negative MTR), plateau, (0 MTR), and phase-out (positive MTR)

5) States have added EITC components to their income taxes [in general a percentage of the Fed EITC, great source of natural experiments, understudied bc CPS too small]
A: EITC Schedule in 2018

The diagram shows the relationship between annual credit (USD) and earnings (USD) for different numbers of children.

- **0 children**: The credit increases with earnings up to a certain point and then decreases.
- **1 child**: Similar pattern as 0 children but with a higher peak.
- **2 children**: The peak is higher than for 1 child.
- **3+ children**: The peak is the highest among the categories shown.

The x-axis represents earnings in USD, ranging from 0 to 60,000, and the y-axis represents annual credit (USD), ranging from 0 to 6,000.
Notes: This figure shows federal EITC parameters for different family sizes. Panel A shows the 2018 EITC schedule as a function of total family earnings for families with 0, 1, 2, and 3+ EITC-eligible children. Panel B shows the maximum annual credit for families with 0, 1, 2, and 3+ EITC-eligible children between 1968 and 2018, in 2018 USD.
Labor Force Participation of Single Women
With and Without Children

![Graph showing labor force participation of single women with and without children over years.](https://via.placeholder.com/150)

Source: Kleven (2018)
Labor Force Participation of Single Women
With and Without Children

50 years of relative stability, apart from these 5 years

Unemployment Rate

Labor Force Participation (%)

Year

With Children Without Children

Annual Employment
Low Education

Source: Kleven (2018)
Labor Force Participation of Single Women
With and Without Children

50 years of relative stability, apart from these 5 years

Source: Kleven (2018)
Labor Force Participation of Single Women
With and Without Children

Tax Reduction Act of 1975 TRA86 OBRA90 OBRA93 ARRA

Unemployment Rate

Labor Force Participation (%)

Year

With Children Without Children

Annual Employment Low Education

Source: Kleven (2018)
Labor Force Participation of Single Women
With and Without Children

Source: Kleven (2018)
Labor Force Participation of Single Women
With and Without Children

Source: Kleven (2018)
Labor Force Participation of Single Women
By Number of Children

Tax Reduction Act of 1975 TRA86 OBRA90 OBRA93 ARRA

Labor Force Participation (%)

Source: Kleven (2018)
Labor Force Participation of Single Women
By Number of Children

Source: Kleven (2018)
Labor Force Participation of Single Women

By Number of Children

- Tax Reduction Act of 1975
- TRA86
- OBRA90
- OBRA93
- ARRA

But no increase here by those with 3+ kids

40 50 60 70 80 ...
68 70 72 74 76 78 ...
0 children 1 child 2 children 3+ children

Annual Employment Low Education
22 / 167

Source: Kleven (2018)
Difference-in-Differences: Treated vs Control States (With Kids)

3-Year Effect = -1.21

38 / 111
WELFARE REFORM AND EITC EXPANSION: LABOR SUPPLY

Incredible increase in labor force participation of single mothers during the 1990s when welfare reform and EITC expansion happened.

Unlikely that the EITC can explain it because other EITC changes haven’t generated such large effects.

Sociological evidence shows that welfare reform “scared” single mothers into working.

Single moms in the US were suddenly expected to work.

Kleven (2019): Maybe a unique combination of EITC reform, welfare reform, economic upturn, and changing social norms lead to this shift.
Notes: This figure shows DiD event studies of the 1993 reform for waiver states (black series) and non-waiver states (blue series). Specifically, the series show estimates of the DiD coefficient $\gamma_t$ from specification (2), implemented separately on states that ever approved statewide waiver legislation and those that did not. Both series include controls for demographics and unemployment. From Table A.3 in the appendix, there were 13 states without any statewide waiver legislation: Alabama, Alaska, District of Columbia, Kansas, Kentucky, Louisiana, Nevada, New Mexico, New York, Oklahoma, Pennsylvania, Rhode Island, and Wyoming. The extensive margin outcome is weekly employment. The sample includes single women aged 20-50 using the March and monthly CPS files combined. The 95% confidence intervals are based on robust standard errors clustered at the individual level.
BUNCHING AT KINKS (SAEZ AEJ-EP’10)

Key prediction of standard labor supply model: individuals should bunch at (convex) kink points of the budget set

1) The only non-parametric source of identification for intensive elasticity in a single cross-section of earnings is amount of bunching at kinks creating by tax/transfer system

2) Saez ’10 develops method of using bunching at kinks to estimate the compensated income elasticity

Formula for elasticity: \( \varepsilon^c = \frac{dz/z^*}{dt/(1-t)} = \frac{\text{excess mass at kink}}{\text{change in NTR}} \)

⇒ Amount of bunching proportional to compensated elasticity

Blomquist-Newey 2017: Bunching method requires making assumptions on counterfactual density (but testable using tax changes see Londono-Avila ’20 below)
elasticity would no longer be a pure compensated elasticity, but a mix of the compensated elasticity and the uncompensated elasticity. Four points should be noted. First, the larger the behavioral elasticity, the more bunching we should expect.

Unsurprisingly, if there are no behavioral responses to marginal tax rates, there

Panel A. Indifference curves and bunching

Before tax income $z$

After-tax income $c = z - T(z)$

Individual $L$ indifference curve

Individual $H$ indifference curves

Slope $1 - t - dt$

Slope $1 - t$

Individual $L$ chooses $z^*$ before and after reform
Individual $H$ chooses $z^* + dz^*$ before and $z^*$ after reform

$dz^*/z^* = e dt/(1 - t)$ with $e$ compensated elasticity

Source: Saez (2010), p. 184
Elasticity would no longer be a pure compensated elasticity, but a mix of the compensated elasticity and the uncompensated elasticity. Four points should be noted. First, the larger the behavioral elasticity, the more bunching we should expect. Unsurprisingly, if there are no behavioral responses to marginal tax rates, there would be no bunching. Panel A displays the effect on earnings choices of introducing a (small) kink in the budget set by increasing the tax rate $t$ by $dt$ above income level $z^*$. Individual $L$ who chooses $z^*$ before the reform stays at $z^*$ after the reform. Individual $H$ chooses $z^* + dz^*$ before the reform and was choosing $z^*$ after the reform. Panel B depicts the effects of introducing the kink on the earnings density distribution. The pre-reform density is smooth around $z^*$. After the reform, all individuals with income between $z^*$ and $z^* + dz^*$ before the reform, bunch at $z^*$, creating a spike in the density distribution. The density above $z^* + dz^*$ shifts to $z^*$ (so that the resulting density and is no longer smooth at $z^*$).

Source: Saez (2010), p. 184
Before reform: linear tax rate $t_0$, density $h_0(z)$

After reform: tax rate $t_0$ below $z^*$
Tax rate $t_1$ above $z^*$ ($t_1 > t_0$), density $h(z)$

$B = H^* - (H^- + H^+) = \text{excess bunching}$

Figure 2. Estimating Excess Bunching Using Empirical Densities
BUNCHING AT KINKS (SAEZ AEJ-EP’10)

1) Uses individual tax return micro data (IRS public use files) from 1960 to 2004

2) Advantage of dataset over survey data: very little measurement error

3) Finds bunching around:

   a) First kink point of the Earned Income Tax Credit (EITC), especially for self-employed

   b) At threshold of the first tax bracket where tax liability starts, especially in the 1960s when this point was very stable

4) However, no bunching observed around all other kink points
EITC Amount as a Function of Earnings

- Subsidy: 34%
- Subsidy: 40%
- Phase-out tax: 16%
- Phase-out tax: 21%

Source: Federal Govt
indexes earnings to 2008 using the IRS inflation parameters, so that the EITC kinks are perfectly aligned for all years.

Two elements are worth noting in Figure 3. First, there is a clear clustering of tax filers around the first kink point of the EITC. In both panels, the density is maximum exactly at the first kink point. The fact that the location of the first kink point differs between EITC recipients with one child, versus those with two or more children, constitutes strong evidence that the clustering is driven by behavioral responses to the EITC as predicted by the standard model. Second, however, we cannot discern any

Panel A. One child

Panel B. Two children or more

Figure 3. Earnings Density Distributions and the EITC

Notes: The figure displays the histogram of earnings (by $500 bins) for tax filers with one dependent child (panel A) and tax filers with two or more dependent children (panel B). The histogram includes all years 1995–2004 and inflates earnings to 2008 dollars using the IRS inflation parameters (so that the EITC kinks are aligned for all years). Earnings are defined as wages and salaries plus self-employment income (net of one-half of the self-employed payroll tax). The EITC schedule is depicted in dashed line and the three kinks are depicted with vertical lines. Panel A is based on 57,692 observations (representing 116 million tax returns), and panel B on 67,038 observations (representing 115 million returns).

Source: Saez (2010), p. 191
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Similarly, we cannot discern any gap in the distribution of earnings around the concave kink point where the EITC is completely phased-out. This differential response to the first kink point, versus the other kink points, is surprising in light of the standard model predicting that any convex (concave) kink should produce bunching (gap) in the distribution of earnings.

In Figure 4, we break down the sample of earners into those with nonzero self-employment income versus those zero self-employment income. Panel A reports the density for tax filers with one dependent child and panel B for tax filers with two or more dependent children. The charts include all years 1995–2004. The bandwidth is $400 in all kernel density estimations. The fraction self-employed in 16.1 percent and 20.5 percent in the population depicted on panels A and B (in the data sample, the unweighted fraction self-employed is 32 percent and 40 percent). We display in dotted vertical lines around the first kink point the three bands used for the elasticity estimation with $\delta = $1,500.

Source: Saez (2010), p. 192
systematic clustering around the second kink point of the EITC. Similarly, we cannot discern any gap in the distribution of earnings around the concave kink point where the EITC is completely phased-out. This differential response to the first kink point, versus the other kink points, is surprising in light of the standard model predicting that any convex (concave) kink should produce bunching (gap) in the distribution of earnings.

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Source: Saez (2010), p. 192
WHY NOT MORE BUNCHING AT KINKS?

1) True intensive elasticity of response may be small

2) Randomness in income generation process: Saez (1999) shows that year-to-year income variation too small to erase bunching if elasticity is large

3) Frictions: Adjustment costs and institutional constraints (Chetty, Friedman, Olsen, and Pistaferri QJE’11)

4) Information and salience
EITC BEHAVIORAL STUDIES

Evidence of response along extensive margin but little evidence of response along intensive margin (except for self-employed) ⇒ Possibly due to lack of understanding of the program

Qualitative surveys show that:

Low income families know about EITC and understand that they get a tax refund if they work

However very few families know whether tax refund ↑ or ↓ with earnings

Such confusion might be good for the government as the EITC induces work along participation margin without discouraging work along intensive margin (Liebman-Zeckhauser ’04, Rees-Jones and Taubinsky ’16)
Use US population wide tax return data since 1996 (through IRS special contract)

1) Substantial heterogeneity in fraction of EITC recipients bunching (using self-employment) across geographical areas

⇒ Information on EITC varies across areas and grows overtime

2) Places with high self-employment EITC bunching display wage earnings distribution more concentrated around plateau

3) Omitted variable test: use birth of first child to test causal eff‘EITC on wage earnings

⇒ Evidence of wage earnings response to EITC along intensive margin
Earnings Distributions in Lowest and Highest Bunching Deciles

Source: Chetty, Friedman, and Saez NBER'12
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 1996

Source: Chetty, Friedman, and Saez NBER'12
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 1999

Source: Chetty, Friedman, and Saez NBER'12
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2002

Source: Chetty, Friedman, and Saez NBER'12
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2005

Source: Chetty, Friedman, and Saez NBER'12
Fraction of Tax Filers Who Report SE Income that Maximizes EITC Refund in 2008

Source: Chetty, Friedman, and Saez NBER'12
Income Distribution For Single Wage Earners with One Child

Is the EITC having an effect on this distribution?

Source: Chetty, Friedman, and Saez NBER'12
Income Distribution For Single Wage Earners with One Child
High vs. Low Bunching Areas

Source: Chetty, Friedman, and Saez NBER'12
Earnings Distribution in the Year Before First Child Birth for Wage Earners

Percent of Individuals

- 2%
- 4%
- 0%
- 6%

Wage Earnings

- Lowest Sharp Bunching Decile
- Middle Sharp Bunching Decile
- Highest Sharp Bunching Decile

Source: Chetty, Friedman, and Saez NBER'12
Earnings Distribution in the Year of First Child Birth for Wage Earners

Source: Chetty, Friedman, and Saez NBER'12
IMPLICATIONS OF ROLE OF INFORMATION

Empirical work:

Information should be a key explanatory variable in estimation of behavioral responses to govt programs

When doing empirical project, always ask the question: did people affected understand incentives?

Cannot identify structural parameters of preferences without modeling information and salience

Normative analysis:

Information is a powerful and inexpensive policy tool to affect behavior

Should be incorporated into optimal policy design problems
VALUE OF ADMINISTRATIVE DATA

Key advantages of admin data (in most advanced countries such as Scandinavia):

1) Size (often full population available)

2) Longitudinal structure (can follow individual across years)

3) Ability to match wide variety of data (tax records, earnings records, family records, health records, education records)

US is lagging behind in terms of admin data access [hard to match across agencies]

Private sector also generates valuable big data (Google, Credit Bureaus, personnel/health data from large companies)
ADVANCE EITC

Recipients get EITC with tax refund in a single annual refund in Feb year $t + 1$ which seems suboptimal: (a) free interest loan to govt and (b) harder to smooth consumption [surveys show that primary use of tax refund is to pay overdue bills]

Tax filers have option to use Advance EITC to get part of EITC in the paycheck by filing a W5 form with employer [reverse of tax withholding]: take up extremely low (<2%)

Possible explanation: (a) Information, (b) Lack of employer cooperation, (c) Risk of owing taxes if not EITC eligible, (d) Tax filers like big refunds, (e) Inertia (default is no Advance EITC)
ADVANCE EITC

Jones AEJ-AP’10 carries a randomized experiment with large employer to encourage take-up and gets significant but very small take-up effect suggesting that (a) [Information] and (b) [Employer cooperation] cannot explain low take-up

(d) [Love of refunds] seems plausible but (1) not supplied by market absent refunds [employers could also pay part of wages as annual lumpsum], (2) A-EITC use has not increased with EITC expansions

(c) [Risk of owing taxes] and (e) [Inertia] are likely part of the explanation

Interesting research topic: Have big tax refunds fueled low income credit [tax refund loans, payday loans, etc.]? Are big refunds useful forced saving mechanisms?

Biden expanded Child Tax Credit was 50% monthly
Taxes and transfers sometimes also generate notches (=discontinuities) in the budget set.

Such discontinuities should create bunching (and gaps) in the resulting distributions.

Kleven and Waseem QJE’13 pioneered tax notch analysis in the case of the Pakistani income tax where average tax rate jumps.

⇒ Bunching below the notch and gap in density just above the notch.

Recently Londono-Velez and Avila (2020) use notch analysis to study wealth tax in Columbia.

They show clean prior-year counterfactual overcoming the Blomquist et al. ’21 critique. (With a single cross-section, need to make assumptions about the counterfactual distribution (which is unknown)).
B  Density Distributions

Density

bunching

density hole

pre-notch density

post-notch density

Earnings $z$
Figure 1: The Personal Wealth Tax Schedule in Colombia

(a) Wealth Tax Liability as a Function of Reported Wealth (FY 2010)
(b) Evolution of Statutory Annual Wealth Tax Rates by Bracket Cutoff

Tax rate $\tau$

Bracket cutoff:
- 1 billion pesos
- 2 billion pesos
- 3 billion pesos
- 5 billion pesos

Source: Table A.1
Figure 2: Distribution of Reported Net Worth in 2009 (Before Reform) and 2010 (After Reform)

Notes: This figure overlays the distribution of tax filers by reported net wealth before and after a reform introduced two wealth tax notches at 1 and 2 billion pesos (red vertical lines), as depicted in Figure 1. These notches imply that wealth tax liability jumps discontinuously, as illustrated in Figure 1. The figure shows that the distribution of individuals is smooth in the absence of wealth tax notches (2009). The two notches result in the immediate emergence of excess mass below the notch points, and corresponding missing mass just above them (2010). This
BUNCHING AT NOTCHES: ELASTICITY ESTIMATION

With optimization frictions (lack of information, costs of adjustment), a fraction of individuals fail to respond to notch

Kleven-Waseem use empirical density in the theoretical gap area to measure the fraction of unresponsive individuals

This allows them to back up the frictionless elasticity (i.e. the elasticity among responsive individuals)

The frictionless elasticity is much higher than the reduced form elasticity but remains still relatively modest
MANY RECENT BUNCHING STUDIES

Bunching method applied to many settings with nonlinear budgets with convex kink points or notches (Kleven ’16 survey):

- Individual tax (Bastani-Selin ’14 Sweden, Mortenson-Whitten ’19 US)
- Payroll tax (Tazhidinova ’15 on UK)
- Corporate tax (Devereux-Liu-Loretz ’14, Bachas-Soto ’17)
- Wealth tax (Seim ’17, Jakobsen et al. ’17, Londono-Velez and Avila ’20)
- Health spending (Einav-Finkelstein-Schrimpf ’13 on Medicare Part D)
- Retirement savings (401(k) matches)
- Retirement age (Brown ’13 on California Teachers)
- Housing transactions (Best and Kleven, 2017)
- Audit probabilities (Al-Karablieh, Koumanakos, and Stantcheva 2021)

General findings: (1) clear bunching when information is salient and outcome easily manipulable; comes most often from avoidance/evasion rather than real behavior (2) bunching is almost always small relative to conventional elasticity estimates
CORPORATE TAX EVASION: EVIDENCE FROM BUNCHING

Al-Karablieh, Koumanakos, and Stantcheva use universe of Greek tax returns to study how firms respond to a “self-assessment” (amnesty-type program)

If firms report a profit margin above a threshold, they are exempt from audit in that year.

Profit margin = profit/revenue

How can a firm meet its profit margin?

What is the desirable response for the tax authority? Which response is undesirable?

Possible pitfalls of this program?
Figure 3: Bunching at the €300,000 Revenue Cutoff

excess mass = 0.685
Figure 4: Graphical evidence for responses to self-assessment

A. Distribution of profit margins in years in which firms do not self assess
Figure 4: Graphical evidence for responses to self-assessment

A. Distribution of profit margins in years in which firms self assess
Figure 5: Profit margins of firms in the accommodation and food industry

In years in which they do not self-assess

In years in which they self-assess
Figure 6: Event study of responses to self-assessment

A. Taxable Profit Margins

B. Log Revenue

C. Log Taxable Profits
Intertemporal Labor Supply: High Frequency

Frisch elasticity $e^F$: changing wages in a single period and keeping marginal utility of income $\lambda$ constant

Compensated static elasticity $e^C$: changing wages in all periods but keeping utility constant

Uncompensated static elasticity $e^U$: changing wages in all periods with no compensation

Theoretically: $e^F > e^C > e^U$

Frisch elasticity is of central interest for calibration of macro business cycle models:

Real business cycle model requires huge elasticity to generate realistic employment fluctuations
INTERTEMPORAL SUBSTITUTION: TAX HOLIDAY IN ICELAND

In 1987, Iceland transitioned from paying taxes on previous year’s income to current income.

To avoid double taxation during transition, no tax charged over 1987 incomes.

Average tax rate of 14.5% in 1986, 0% in 1987, 8% in 1988.

Reform announced in late 1986 ⇒ unanticipated temporary tax change.

Temporary change in incentives ⇒ ideal quasi-experiment to intertemporal substitution elasticity (work hard in 1987, take a break in 1986 or 1988).

Bianchi et al. AER’01 look at employment effects [hard to know what counterfactual is].

Sigurdsson (2020) compares high (big tax cut) vs. low earners (small tax cut) and finds larger response among high earners [but possible that high earners are more elastic to start with].
Figure 1a: 1987 Tax Holiday in Iceland
Tax Holiday in Swiss Cantons

Martinez, Saez, Siegenthaler '21 study tax holidays in Swiss cantons also created by a transition to pay-as-you earn

Key advantage: different cantons transitioned at different times (creating staggered tax holidays across cantons)

Key findings:

(a) precise zero effect on extensive margin

(b) some effects on intensive margin for high wage earners and self-employed (possibly avoidance rather than real)

Why smaller effects in Switzerland than Iceland? Iceland sold tax holiday as opportunity to work more (Switzerland did not)
Transition from retrospective taxation to annual pay-as-you-earn

- Reasons: modernizing, simplifying and harmonizing
- Side effect: incomes earned during the two years prior to the change remained *untaxed* (blank years, tax holiday)

|--------|------|------|------|------|------|------|------|------|

- Cantons chose different years to change: 1999, 2001, and 2003
Timing of the Reform

Blank Years in Each Canton

- 1997/98, federal and cantonal
- 1997/98 federal, 1998 cantonal
- 1999/00, federal and cantonal
- 1999/00 federal, 2000 cantonal
- 1999/00, federal tax only
- 2001/02, federal and cantonal
- No blank years

Map showing regions with different years for the reform.
Average Income Tax Rates over Time

Total federal, cantonal and municipal tax, single taxpayer; weighted by municipality population.
Marginal Income Tax Rates over Time

Marg. tax rate in % at a gross income of 100K CHF (real value 2010)


Tax Holiday in...

Total federal, cantonal and municipal tax, single taxpayer; weighted by municipality population.
Employment Rate: Men (age 20-60)

Wage employees/population (in %)

Data source: AHV-STATPOP
Employment Rate: Women (age 20-60)

Wage employees/population (in %)


1997-98 1998 1999-00 2000 2001-02

Tax holiday in...
Average Wage Earnings: High-income Employees

High income: avg. real wage earnings in 1994-1996 > 100k CHF/year
Mean Self-employment Earnings (excluding zeros)

Data source: AHV-STATPOP
SOCIAL DETERMINANTS OF LABOR SUPPLY

Concern that taxes funding social state could discourage work

Standard econ view: labor supply $l(w, R)$ coming out of
\[ \max_{c, l} u(c, l) \quad \text{st} \quad c = wl + R \] is highly incomplete

Social determinants of labor supply:

a) Youth labor is regulated by labor laws/education
b) Old age labor regulated by retirement programs
c) Female market labor driven by norms + child care policy
d) Hours of work regulated by overtime + vacation mandates

Social labor supply with “disutility” for youth, old, overtime labor
Employment Rates of Men by Age, 2019

Source: OECD database online. Employment to population ratios.

Source: Saez AEA-PP’21
Employment Rates of Women by Age, 2019

Source: OECD database online. Employment to population ratios.

Source: Saez AEA-PP'21
Employment Rates of Men and Women, aged 25-54

Source: OECD database online.

Source: Saez AEA-PP'21
US female labor force participation, age 16-64


25% increase in 1943-1945 during WW2 planned economy

Source: Saez AEA-PP'21
Average Annual Hours of Work of Employees

Source: Saez AEA-PP'21

- United States
- France

US has 40 hour/week and no mandatory paid vacation

1968: 4th week of paid vacation
1982: 5th week + 39 hours/week
2000-2: 35 hours/week

Source: OECD database online. Includes all ages, genders, and part-time, full-time, overtime.
Figure 2. Average Weekly Hours Worked per Person, by Age Group

B. Males

C. Females

Ramey and Francis AEJ'09

Source: Authors' estimates, based on information from Kendrick (1961, 1973), the census, and the CPS.
LONG-TERM EFFECTS: EVIDENCE FROM THE ISRAELI KIBBUTZ

Abramitzky ’18 book based on series of academic papers

Kibbutz are egalitarian and socialist communities in Israel, thrived for almost a century within a more capitalist society

1) Social sanctions on shirkers effective in small communities with limited privacy

2) Deal with brain drain exit using communal property as a bond

3) Deal with adverse selection in entry with screening and trial period

4) Perfect sharing in Kibbutz has negative effects on high school students performance but effect is small in magnitude (concentrated among kids with low education parents)
LONG-TERM EFFECTS: EVIDENCE FROM THE ISRAELI KIBBUTZ

Abramitzky-Lavy ECMA’14 show that high school students study harder once their kibbutz shifts away from equal sharing.

Uses a DD strategy: pre-post reform and comparing reform Kibbutz to non-reform Kibbutz. Finds that

1) Students are 3% points more likely to graduate

2) Students are 6% points more likely to achieve a matriculation certificate that meets university entrance requirements

3) Students get an average of 3.6 more points in their exams

Effect is driven by students whose parents have low schooling; larger for males; stronger in kibbutz that reformed to greater degree.
CULTURE OF WELFARE ACROSS GENERATIONS

Conservative concern that welfare promotes a culture of dependency: kids growing up in welfare supported families are more likely to use welfare

Correlation in welfare use across generations is obviously not necessarily causal

Dahl, Kostol, Mogstad QJE’2014 analyze causal effect of parental use of Disability Insurance (DI) on children use (as adults) of DI in Norway

Identification uses random assignment of judges to denied DI applicants who appeal [some judges are severe, some lenient]

Find evidence of causality: parents on DI increases odds of kids on DI over next 5 years by 6 percentage points

Mechanism seems to be learning about DI availability rather than reduced stigma from using DI [because no effect on other welfare programs use]
Figure III
Effect of Judge Leniency on Parents (First Stage) and Children (Reduced Form)

Baseline sample, consisting of parents who appeal an initially denied DI claim during the period 1989–2005 (see Section III for further details). There are 14,722 individual observations and 79 different judges. Judge leniency based on all cases a judge has ever handled, and not just the cases in our estimation sample. Panel A: Solid line is a local linear regression of parental DI allowance on judge leniency. Panel B: Solid line is a local linear regression of child DI receipt on their parent’s judge leniency measure. All regressions include fully interacted year and department dummies. The histogram of judge leniency is shown in the background of both figures (top and bottom 1% excluded from the graph). Dashed lines represent 90% confidence intervals.
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