DO OLDER TAXPAYERS RESPOND TO THE TAXATION OF SOCIAL SECURITY BENEFITS?

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Policy Abstract/Abstract

The taxation of Social Security benefits creates very high marginal tax rates that can discourage work among older people. This paper develops a model of labor supply and the Social Security claiming decision. While previous research found that the labor supply of retirement-age workers is significantly affected by the Social Security earnings test and the implicit taxes created by the Social Security benefit formulas, we find no evidence that taxation of benefits affects individuals' decisions to work or claim Social Security benefits. This could be due to data limitations, individuals' lack of understanding about the taxation of benefits, or true non-response, and warrants further investigation.

Introduction

Social Security benefits are taxed under a complex regime that raises marginal effective tax rates by up to 85 percent. The maximum effective tax rate of 46.3 percent is significantly higher than the current top statutory income tax rate (35 percent), and applies to moderate income households. The tax on benefits is effectively a Social Security earnings test (SSET) but, unlike the SSET, applies at all ages with no actuarial adjustment to future benefits. While previous research found that the labor supply of retirement-age workers is significantly affected by the SSET (Friedberg 2000; Gustman and Steinmeier 2005; Benitez-Silva and Heiland 2007; Song and Manchester 2007; Heider and Loughran 2008; Engelhardt and Kumar 2009; Friedberg and Webb 2009) and the implicit taxes created by the SS benefit formulas (Liebman, Luttmer, and Seif 2009), the taxation of benefits has been thus far largely ignored. One exception is Liebman and Goodman (2008), who looked at the taxation of Social Security as a form of means testing. To our knowledge, nobody has estimated behavioral responses to the taxation of benefits. This is a potentially important oversight. If taxpayers understand the rules, one would be expect them to be even more sensitive to this work disincentive than to the SSET, since there is no subsequent increase in Social Security benefits.[1] Early retirees may be subject to both the SSET and SS benefit taxation, so the effective work disincentive may be quite large. If the tax is inefficient, reform options might exist that could bolster the trust fund, extend older people's attachment to the labor force, significantly reduce tax compliance costs for older workers, and raise overall economic welfare.

The paper continues as follows. Section 1 explains the tax treatment of Social Security benefits in detail. Section 2 sets up the labor supply model. Section 3 discusses the data. Section 4 presents the specification tests for bunching and claiming age. Section 5 presents our results for labor force participation and hours worked. Section 6 concludes by discussing the implications of our findings for tax reform.

[1] Moreover, this tax affects nonlabor income as well as earnings and so can affect decisions about when to realize capital gains, for example. As noted in Burman (1999), the taxation of Social Security can have disproportionate effects on effective capital gains tax rates because it adds up to 85 percent of the statutory tax rate to the reduced long-term capital gains tax rate. Unfortunately, our dataset does not have information about capital gains, so we will be focusing on labor income in our analysis.

1. Taxation of Social Security Benefits

OASDI benefits may be subject to income taxation if modified adjusted gross income (MAGI) [2] exceeds $25,000 for single ($32,000 for married) households. Above that threshold, the taxable portion of benefits phases in at a 50 percent rate until MAGI reaches a second threshold ($34,000 for singles/ $44,000 for married), beyond which the phase-in rate increases to 85 percent of benefits included in income. The Greenspan Commission created the 50 percent phase-in to shore up Social Security's finances in 1983. All the income tax revenues attributable to the taxation of benefits were originally earmarked for the OASDI trust fund. In 1993, with Medicare facing a shortfall, the 85-percent phase-in was enacted and the additional revenues (over and above the original 50-percent phase-in) were allocated to the HI trust fund. The thresholds for taxation have been fixed in nominal terms since their inception. Since the thresholds are not adjusted for inflation, they decrease in real terms over time, unlike federal income tax brackets and many other income tax parameters. As a result, taxation of Social Security affects an increasing proportion of older workers over time pushing people into higher tax brackets. This process of jumping into higher tax brackets due to inflation—even as real income remains unchanged—is known as "bracket creep."

The partial taxation of benefits significantly raises marginal tax rates for many taxpayers. Taxpayers with low Social Security benefits or modest amounts of other income are not affected. However, as either benefits or other income increase, marginal tax rates may increase quite dramatically. For example, a single person with $15,000 of non-Social Security income and $19,900 of Social Security benefits has none of her Social Security included in income; her marginal income tax rate equals the statutory rate of 10 percent. If her Social Security benefit increases by $100, her marginal tax rate would increase to 15 percent.

Figure 1 shows the shape of the effective marginal tax rate schedule facing a taxpayer aged 65 or older with $20,000 in Social Security benefits. It is marked by significant discontinuities—much larger than under the regular income tax. Over this range of income, a taxpayer would ordinarily face three marginal rates—10, 15, and 25 percent. However, because of the partial inclusion of Social Security benefits, three additional effective rates are created.

[2] MAGI is defined as adjusted gross income (AGI) plus tax-exempt interest plus one-half of Social Security benefits.

The highest-income taxpayers face a marginal rate more than 20 percentage points lower than those with lower incomes. This creates a nonconvexity in the household budget constraint.[3]

The substantial kinks in the tax schedule could create clustering of households at the kink points, and potentially discourage labor supply at both the extensive and intensive margins. Although taxpayers with very low and very high nonlabor income are likely to be unaffected, taxpayers whose earnings would be subject to partial taxation might be less likely to work than other similar taxpayers. Secondary earners may face especially strong disincentives if the primary earner's income puts the second earner in the phase-in range.

The tax treatment of benefits could also affect decisions about when to begin claiming Social Security. The steeply rising marginal tax rate schedule creates an incentive for many people to claim benefits early, getting a reduced benefit over more years. Individuals born after 1942 can reduce their annual benefit by 25 percent or more by claiming at age 62 rather than the full retirement age and fully or partially avoid taxation of Social Security benefits. As a result, the adjustment for delayed retirement may no longer be actuarially fair when taxes are considered. On the other hand, some taxpayers may have an incentive to delay claiming Social Security benefits. If a worker reaches the full retirement age and expects to keep working for a few more years after which his non-Social Security income would drop significantly, he may elect to delay claiming Social Security benefits if the future drop in income means that much less of his benefits would be subject to tax. In this case, the after-tax value of delaying retirement is better than actuarially fair, even if before tax, the trade-off is neutral.[4]

Finally, it should be noted that the very complicated taxation of Social Security benefits might affect behavior much differently than predicted by a pure optimizing model. It is possible that people do not understand how the tax affects marginal tax rates, the incentives on labor supply, or the timing of benefits. If people ignore these incentives, then the tax may be a type of optimal tax—raising revenue with little or no effect on behavior. On the other hand, taxpayers may overreact to misunderstood incentives—magnifying the economic distortion.

[3] This means that an optimizing household with flexibility about hours worked (or other income) would avoid earning income near the last kink point (other income of $38,706) since working either a little more or a little less would increase utility.

[4] Coile et al. (2002) model the timing of claiming Social Security. Even ignoring the taxation of social Security benefits as they do, the decision is very complicated. They present nonlinear simulations for the case of a single earner, leaving the more complex case of dual earners to later research, They find that men generally retire too early compared with the optimal choice.

2. Theoretical Model

We adopt the common approach to analyze labor supply based in a simple static utility maximization framework. Individuals maximize the utility of an aggregate consumption good and leisure subject to a budget constraint:

$$\max U = U(C, L)$$

$$C = wh(1 - \tau) + Y^v$$

where C is consumption, L is leisure, w is the wage rate, h is hours worked, τ is the tax rate, and Y^v is virtual income. The virtual income concept was developed by Hausman (1981) as a way to linearize the concave budget set formed by the progressive tax code. Virtual income is nonlabor income plus the difference between tax that would be collected at a flat tax rate, τ, and the actual tax owed under the progressive rate schedule.

Estimating labor supply models in the context of taxation poses potentially serious difficulties; joint determination of labor supply within a household, a non-linear, non-proportional income tax schedule, unobserved tastes for work that impact the observed wages that may be age-varying, and measurement error in the marginal tax rate and wages. Further, there is no obvious quasi-experiment to exploit to help with identification; the law has been unchanged since its inception. The only source of exogenous variation is the real decline in the thresholds for taxation, which causes more and more seniors to be subject to the tax over time. Thus, instead of estimating a structural model, we follow Eissa and Hoynes (2004) and estimate reduced-form hours of work equations that depend on net of taxes wages and virtual income.

Addressing the selection into work is likely even more important in this context because we are examining the decision to work, and how much to work, after claiming Social Security benefits. We model the participation decision as a reduced form probit model:

$$LFP_{it} = \alpha_0 + \alpha_1 X_{it} + \delta_t + \epsilon_{it} \quad (1)$$

where X is a vector of demographic variables, including age, age squared, gender, marital status, education, self-reported health status, number of dependents, homeownership status, job characteristics, and census division. δ is a vector of year-of-interview indicator variables. The error term is assumed to have a standard normal distribution, so we can estimate the parameters consistently using probit maximum likelihood. Using this model, we employ the Heckman selection correction by calculating the inverse mills ratio, and including it in the hours of work equation.

We assume that the hours of work decision is continuous and therefore depends on the log of the net of marginal tax wage (w^n) and log of virtual income (y^v), once participation in the labor force has been determined. We assume that married individuals treat their spouses' earnings as given, and the net of tax wages and virtual income are calculated including spouse's income in nonlabor income. Specifically, the annual hours worked equation is:

$$\ln(H_{it}) = \beta_0 + \beta_1 X_{it} + \gamma_1 \ln(w_{it}^n) + \gamma_2 \ln(y_{it}^v) + \beta_2 IMR_{it} + \beta_3 SSR_{it} + \delta_t + \varepsilon_{it} \quad (2)$$

X is the same vector of demographics as in equation (1), IMR_{it} is the inverse Mills ratio to address the selection into working. SSR_{it} is the Social Security retirement benefits received. The coefficients of interest are γ_1 and γ_2.

We use instrumental variables methods to address the endogeneity of net wage and virtual income. Other work has used gross wage, taxable unearned income (Triest 1987), demographic characteristics (Flood and MaCurdy 1993), tax parameters and demographics (Blundell at al. 1998), and marginal tax rates at set dollar intervals (Eissa and Hoynes 2004). We propose a new take on the Eissa and Hoynes (2004) instrument set, and instead of using set dollar intervals, we calculate the marginal tax rate for different commitments to the labor force; not working at all, working ¼ time, working ½ time, working ¾ time, and working full-time.[5] We assume the wage rate is exogenous to amount of hours worked; thus we simply scale up or down the earnings at the five different levels of labor force attachment for each individual at their observed wage rate, and then use TAXSIM to calculate their marginal tax rates at each different earnings level. The marginal tax rates are computed using the relevant year's tax law, non-labor income (including spousal earnings for married couples), medical expenses, mortgage payments, charitable giving, and family size. This method essentially traces out the relevant segments of the nonlinear budget set.

3. Data

The primary data source for this paper is the *Health and Retirement Study* (HRS) linked to the Social Security Administration *Detail Earnings Records*, to examine how the tax treatment

[5] We define full time as working 8 hours a day, 5days a week and 52weeks a year.

of Social Security benefits impacts labor force participation and the claiming decision. We also use TAXSIM, available from the National Bureau of Economic Research (NBER), to calculate the marginal tax rates for Social Security benefits among individuals above the Full Retirement Age (FRA).[6]

The HRS is a nationally representative study of older Americans conducted every two years. The survey began in 1992 with an initial cohort of 12,652 individuals from 7,607 households where at least one member was born from 1931 to 1941. Additional cohorts were added in 1998 and 2004. By 2008, the sample included over 31,000 individuals in the survey in total, almost 24,500 of them interviewed in 2008.

Table 1 delineates the sample selection criteria. To avoid the interactions between Social Security earnings test and benefit taxation, we restrict the sample to individuals who have reached their FRA after 2000 and use information from waves 6 (2002) through 9 (2008), representing tax years 2001-2007. We also exclude the self-employed, losing approximately 500 observations per wave.[7] Once we eliminate observations that are missing key information in either our dependent or control variables, we end up with 20,454 person-wave observations, representing 7,839 individuals. Approximately 11 percent of the sample reports positive hours of work.

Dependent variables. The HRS contains self-reported information about claiming age, usual number of hours of work per week, and labor force participation, based on whether an individual is currently working for pay.

Independent variables. Typical demographic information, such as marital status, education, race, gender, homeownership, and health status, is available in the HRS. Using the information from the last reported job, we include indicators for the industry (labor intensive; less labor intensive; professional; public administration) and occupation (blue collar; white

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[6] We are grateful to Daniel Feenberg (NBER) for sharing the off-line version of the TAXSIM calculator and Kelly Haverstick (CRR) for her assistance in getting TAXSIM working for this project.

[7] We exclude the self-employed because of data limitations in the HRS and because they are much more likely to misreport earnings to the IRS than wage earners. If they understand the incentives created by taxation of Social Security benefits, their reported earnings could comprise a combination of real responses to the tax incentive and evasion. And it's unclear what they would report to the HRS interviewer in that case.

collar). For those who are currently working, we include an indicator for current retirement plan (regardless of type).

Social Security earnings histories are linked to the survey records of approximately 70 percent of respondents.[8] In order to examine the relationship between claiming Social Security and MAGI, we use the historical earnings for two purposes. First, we use it to determine who is eligible to claim Social Security benefits based on their own work history, with a minimum of 40 covered quarters. We delete individuals who only have access to Social Security retirement through their spouse. Secondly, we use the earning history to calculate potential benefits for anyone who has not yet claimed benefits. We estimate their benefits assuming they will claim in the next year.

While the HRS is often used to estimate labor force participation, hours worked and Social Security claiming decisions, there is one serious drawback from this dataset in this application. Although the wealth and income data is generally considered good, the information is not captured in a way that makes the calculation of marginal tax rates straightforward. The self-reported data provides information on marital status, earnings and Social Security benefit receipt, but we do not know capital gains, state taxes, or even whether a household itemizes deductions. Thus we must make assumptions about these types of parameters before calculating the marginal tax rate a household faces. For simplicity, we follow Rohwedder et al. (2006) where possible. We assume that individuals do not realize any capital gains or losses during the year. We multiply the self-reported mortgage balance by the average interest rate[9] to estimate the mortgage interest paid each year. We also have self-reported information on property taxes paid and medical expenditures. We use self-reported charitable giving where available. For some respondents, charitable giving is only reported in brackets; we use the midpoint of each bracket as the estimate of tax-deductible charitable giving in that case.

State income tax deductions are not reported in the HRS, which creates another dimension of measurement error when simulating federal marginal tax rates TAXSIM will calculate state income taxes, but unfortunately we do not know the state of residence.[10] However, the Census division is included for each record. We calculate marginal federal tax rate for each

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[8] Kapteyn et al. (2006) show that using only subsample of the survey that matches to the administrative data does not introduce bias.

[9] http://www.hsh.com/mtghst.html

[10] State of residence is available in only within a restricted data set, but one that cannot be merged with the Social Security earnings records outside of the University of Michigan due to potential re-identification issues.

state within the census division and then use the average federal tax rate weighted by the number of tax filers in each state. With an estimate of state income taxes, we have the major itemized deductions and can use TAXSIM to estimate the marginal federal income tax rate, τ.

Once we have the tax rate, we compute the net wage in each year (in 2007 dollars), w_{it}^{n} , and virtual income. Virtual income is non-labor income plus the difference between tax collected at a flat tax rate and the actual tax owed under the progressive tax schedule.

Instruments. We calculate the marginal tax rate for 5 different commitments to the labor force; no work, working ¼-time, ½-time, ¾-time, and full-time. The instruments are the natural log of the net-of-tax rate ($1-\tau$). This method essentially traces out the relevant segments of the nonlinear budget set.

Descriptive Statistics. Tables 2 and 3 present descriptive statistics for the subsample that is working after their FRA. Two-thirds of the sample are married and another two-thirds report themselves in good or very good health. Not surprisingly, those still working are more likely to be employed in white-collar occupations and less labor intensive or professional industries.

4. Validity Checks

IV methods would lead to biased estimates of the wage and income effects (γ_1 and γ_2) if there were substantial bunching at the kink-points of the budget set or if there were significant changes in claiming behavior due to the taxation of benefits. Bunching would necessitate data trimming before estimation; changes in claiming behavior would indicate that Social Security benefits would also be endogenous and necessitate another set of instruments. We examine the data for each in turn.

Bunching. We first examine the data for bunching, although previous work suggests this might not be too much of an issue in the U.S. context (Liebman 1997, Saez 2000, Eissa and Hoynes 2004). The first exercise looks for clustering near kink points created by the taxation of Social Security benefits. Figure 2 plots the frequency of MAGI by filing status and Social Security benefit receipt. The data reveal no evidence of bunching around the tax thresholds for individuals collecting Social Security benefits.

Because of the potential for mis-measuring MAGI in the HRS data, we also use information from the 2006 *Statistics of Income* (SOI) public use file, extracting MAGI, total Social Security benefit, taxable Social Security benefit, filing status and the standard deduction. One benefit of this dataset is that there is no measurement error of MAGI. However, there is measurement error on selecting the sample. Since tax records have no age information, we proxy being above age 65 by using the sample that claim the over-65 or blind deduction.[11]

Figure 3 plots the frequency of MAGI by filing status and Social Security benefit receipt, analogous to Figure 2. There is no obvious increase in the mass of returns right before the threshold. If anything, the married filing joint mass seems to fall *after* the taxable thresholds. While the distributions do not indicate perfect bunching right before the two kink points, if there is an element not under perfect control of the taxpayer (e.g., as a random components such as risky returns on assets), or households are not perfectly aware of the precise location of kink points, then we would expect this clustering pattern around the kinks instead of bunching exactly at the kink. To discern such clustering, we follow Saez (2002) and estimate the kernel density instead of just using histograms. We again find no evidence of bunching in either dataset. This suggests that we can estimate the labor supply model on the entire dataset and do not need to drop individuals near the kink-points in the budget set.

Claiming Age. Another potential problem with the IV estimation method arises if individuals change their Social Security claiming ages, and thus their Social Security benefit amounts, because of the income taxation of benefits. This would mean that their Social Security benefits are endogenous in the hours equation as well. To examine this possibility, we first select the subsample that is over the FRA, and sort them based on the distance of MAGI from the first income tax threshold. The rows of Table 4 show the average age, claiming age, and MAGI for those whose MAGI within $30,000 of the first income tax threshold ($25,000 for singles, $34,000 for married filing jointly). At income $20,000-$30,000 below the first threshold, the average claiming age is 63, and almost 87 percent of the sample is currently receiving Social Security benefits. As MAGI increases, the average claiming age is generally increasing, but the differences are quantitatively small and not statistically significant. The percentage receiving

[11] There are approximately 1 million Americans who are legally blind, 60 percent of them are between the ages of 16 and 64 (authors' calculations from the 2006 NHIS). So, out of the 7,991 elderly or blind records in the SOI sample, at most around 600 records are mistakenly included, or 7% of the sample. This method does, however, exclude relatively higher income elderly people who itemize deductions and are thus not eligible for the standard deduction.

Social Security, however, dips just above the MAGI threshold, but the difference is not statistically significant. It is possible that people at that income level are more likely to delay until their incomes dip in retirement.

Next, we perform a simple difference-in-difference test for changes in claiming ages based on income and tax parameters. Due to bracket creep, some individuals become subject to taxation of benefits even if their incomes did not change (in real terms). Thus one can think about being "treated" if bracket creep would mean more of their benefits would be taxed (either 0-50 percent or 50-85 percent) in 2007 if they had the same real income as in 2001, and the "control" as a sample of individuals that are not pushed into a new tax bracket. We empirically test for this by estimating the following regression:

$$Claim\ Age_i = \alpha_0 + \alpha_1 X_{2001} + \alpha_2 Treat_i + \alpha_3 Post + \alpha_4 Treat_i * Post + \varepsilon_i \qquad (3)$$

This very simple difference-in-difference test compares the claiming behavior of those affected by bracket creep. The coefficient of interest is α_4. X is a vector of individual characteristics measured in 2001, such as education, race, marital status, age, and virtual income. We estimate the model on a sample of individuals over the FRA whose marital status does not change between 2001 and 2007 for two sub-groups separately. The "high-income" group has a taxable Social Security benefit in 2001 (N=1,032); the "low-income" does not (N=1,933). These results are presented in the first two columns of Table 5. We find no significant difference in the claiming age due to bracket creep – the coefficient on the interaction term is very small and statistically insignificant in both samples. Because of concerns about errors in the data used to calculate MAGI, we also tried a slightly different definition of "treated" and control groups by expanding the range by 5 percent of AGI separately for low and high income group as well. The cutoff of low and high income group is the median point of the 50% phase-in threshold and 85% phase-in threshold.[12] Within each income group, individuals are taken as treated if their MAGI is in the 5% AGI range around the threshold from both sides. The results are presented in columns 3 and 4 of Table 5. Again, we find no evidence of difference in the claiming age.

5. Results: Effect of Taxation on Working

[12] 32,000+(4,4000-32,000)/2 = 38,000 for married and 25,000+(34,000-25,000)/2 = 29,500 for singles.

Given that these initial tests do not invalidate the estimation method, we then estimate models of labor force participation and hours worked using the HRS. Table 6 presents the results for the reduced form labor force participation equation (equation 1). While age is insignificant, the rest of the covariates are statistically significant determinants of labor force participation and have plausible signs. More education is positively correlated with working, and the individuals with worse self-assessed health are less likely to be working. Individuals working in less labor intensive industries are more likely to be working after their FRA as are individuals with more dependents. Surprisingly, married individuals are less likely to be working, which may be picking up a wealth-effect – married individuals generally are richer, and thus may be more likely to retire earlier. Similar thinking could explain the finding that women are more likely to be working than men, and married women are more likely to be working than married men. Whites are also less likely to work.

Table 7 presents the results for the hours worked estimation (equation 2). Column (1) presents the OLS results, not accounting for selection into working.[13] Column (2) presents the IV results, instrumenting for the net wage with the marginal income tax rates at set earnings levels, a la Eissa (2004). Column (3) presents our preferred results, instrumenting for the net wage based on different levels of attachment to the labor force. Columns (4) and (5) present the results for the female and the male samples, respectively. Column (6) presents the IV estimates with the inclusion of individual fixed-effects.

Column (1) presents the OLS results for hours worked, not controlling for the selection into work nor the endogeneity of the tax rate individuals face, thus the net wage. These estimates suggest that individuals work less in response to their net-of-tax wage. While theory is ambiguous about whether the net-of-tax wage is positively or negatively correlated with uncompensated labor supply because of offsetting income and substitution effects, most empirical research has found a small positive labor supply response. This suggests the possibility of simultaneous equations bias on the coefficient.

Column (2) presents the IV results for the hours equation using instruments suggested in Eissa (2004). These instruments trace out the budget set for the individual using set dollar amount cut-points. One deviation from Eissa we make is using the natural log of the net-of-tax rates instead of the level of tax rates. Here the results are more in-line with expectations. The

[13] Individuals not working are excluded from the estimation.

inverse mills ratio is significant, suggesting that the selection into working is an important consideration. We find that individuals work more when their net-of-tax wage is higher, although the coefficient is only marginally significant. The uncompensated wage elasticity is 0.41, which is relatively high in the tax elasticity literature. In addition, the income effect is negative (as virtual income increases, work hours decrease). The estimated income elasticity is -0.12, which is consistent with the existing literature. While these results fit with our prior beliefs on income and wage elasticities, the instruments employed are weak (the Kleibergen-Paap Wald F statistic - 1.7), giving rise to questions about the validity of these estimates.

Column (3) presents the IV results for the hours equation, but uses instruments based on one's own potential attachment to the labor market. We estimate a set of marginal tax rates for each individual as if they don't work, work ¼ of full time, work ½ of full time, work ¾ of full time and work full time, using their observed wage rate in the computation. Here, our instruments are stronger (Kleibergen-Paap Wald F statistic = 19.7) and comfortably pass the over-identification tests. We continue to find a negative income effect on hours worked, as anticipated, with an estimated income elasticity of -0.19. However, we find no significant impact of the wage on hours worked, suggesting that individuals are not responsive to marginal tax rates, including the taxation of benefits. When we break the sample into women and men (columns 4 and 5) we find results that counter the existing literature. Typically research has shown that married women are the most responsive to tax incentives – attributing this to the fact that they are typically secondary earners in their household. However, here we find that women are non-responsive to their net-of-tax wage. The estimated wage elasticity is consistent with the previous literature, 0.20, but the coefficient is statistically insignificant. In addition, men appear to work longer hours when they have a lower wage, with a statistically insignificant wage elasticity of -0.26. This estimate is within the range estimated in the literature. Pencavel (2002) highlights how sensitive the estimated wage elasticities can be to the control variables, and thus this finding, combined with its marginal statistical significance, warrants further investigation.

Fixed effects regressions. While we control for selection via inclusion of the IMR in the hours equations, there may remain individual time-invariant heterogeneity (such as taste for work) that we are not capturing. Thus we also specify the above relationships using individual fixed-effects models. In this case, our identification comes from changes within households instead of variation between households. Because we must observe each household at least twice, we lose 631 observations. As shown in Table 7, Column 6, however, we find an insignificant wage elasticity.

Difference in Difference results. As robustness check, we run difference-in-difference models for hours worked, similar to those presented earlier for the claiming age. These results are presented in Table 8. Treatment 1 is the same as before: individuals who would be impacted by the bracket-creep if their 2002 real income remained the same in 2008. Treatment 2 widens the definition of treatment due to potential measurement error. We find no evidence, of an impact of bracket creep taxation of Social Security benefits on hours worked, except for low income group in treatment 1, and that estimate is only marginally significant, at the 10 percent level.

6. Conclusions

The taxation of Social Security benefits creates high effective marginal tax rates, which creates incentives for older workers to reduce hours or even leave the work force. If taxpayers respond to those incentives, there could be significant efficiency costs as well as implications for Social Security's and the nation's finances as older workers would be paying less income and payroll taxes. Moreover, the issue is important as the nation considers tax reform options, which might include changing the way Social Security is taxed.

This study is the first to attempt to measure the effects of the taxation of Social Security on older workers' decision to work, how many hours to work, and when to claim Social Security benefits. Using data from the HRS, we estimated traditional labor supply models as well as difference-in-difference estimates and found little or no evidence of response on any of those margins. It may be that the complexity of the taxation of benefits makes it impossible for most old people to respond to rationally. It is also possible that older workers understand the provision but their labor supply is just unresponsive, which is not inconsistent with some evidence from other labor supply models. Unfortunately, though, it is also possible that errors in the HRS tax data make it impossible to measure the effect. Trying to distinguish among these competing possibilities should be the subject of further research (using different data sets).

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Figure 1. Effective Marginal Tax Rates for Single non-Itemizer, Age 66 or Older, With $20,000 of Social Security, by non-Social Security Income, 2010

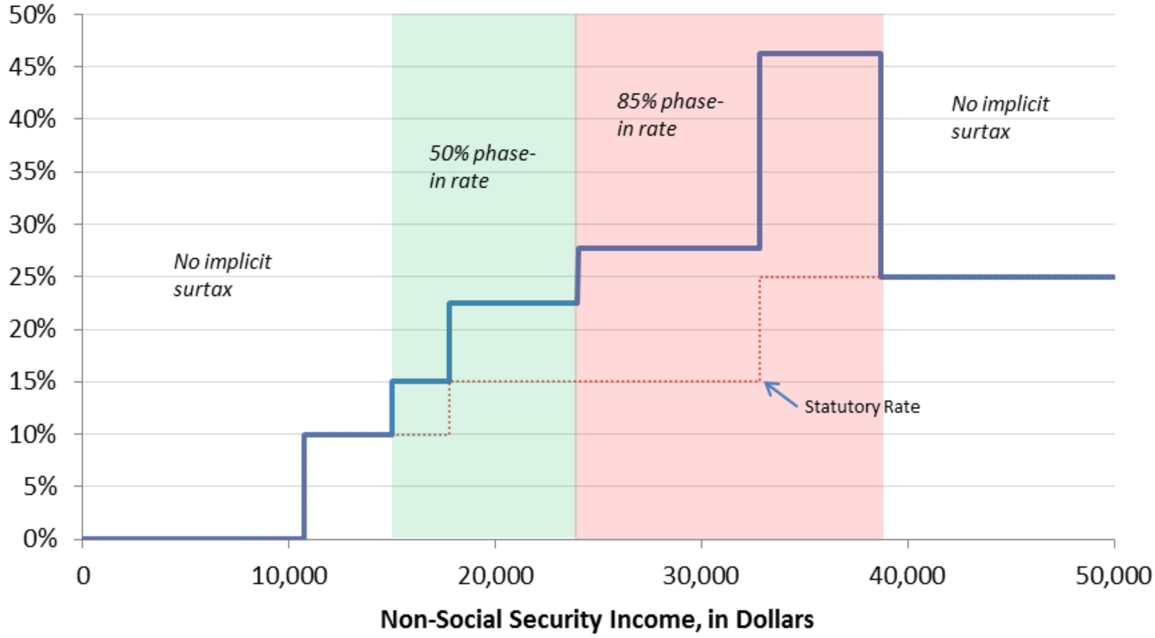
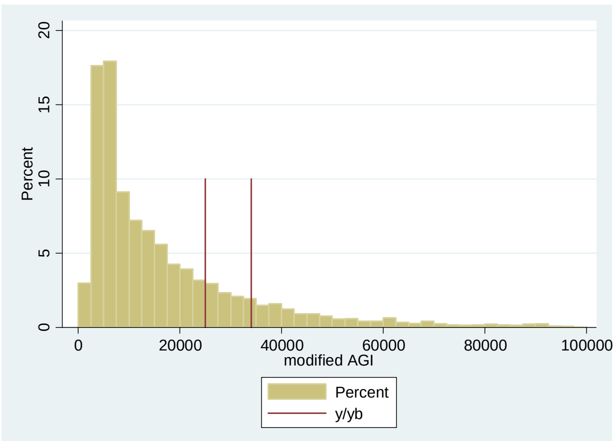
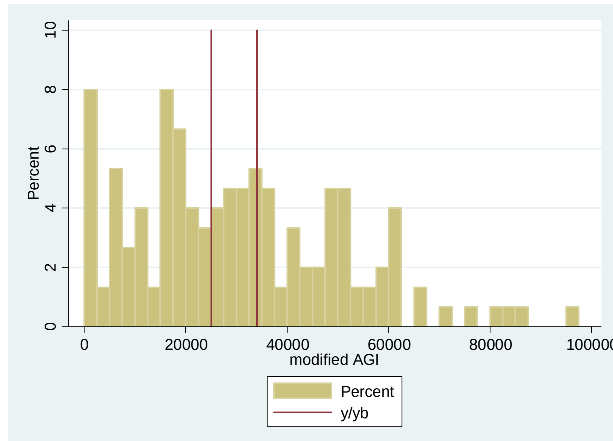


Figure 2: Distribution of MAGI by taxpayer type and Social Security benefit receipt, HRS

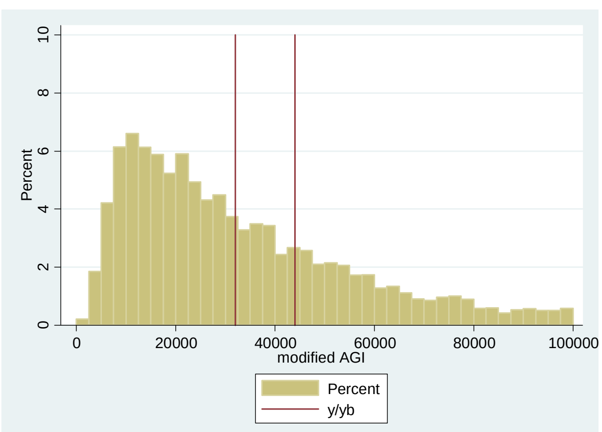
Panel A: Singles with Social Security Benefits (N=5426)



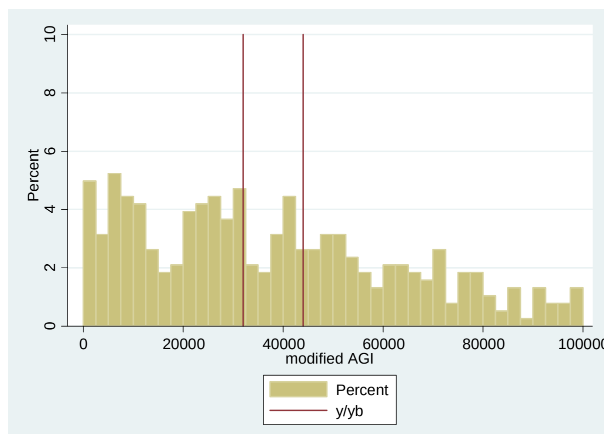
Panel B: Singles without Social Security Benefits (N=15)



Panel C: Married Filing Jointly with Social Security benefits (N=9,592)



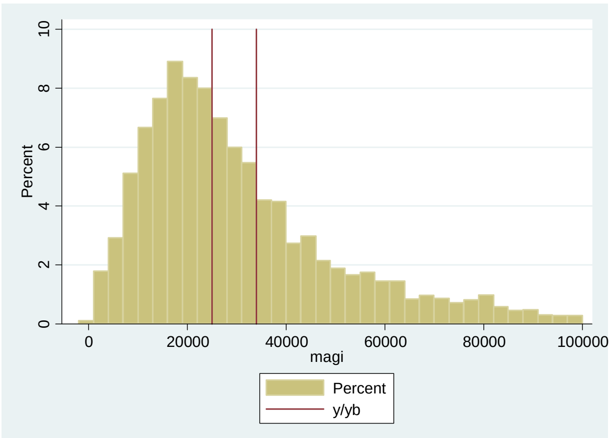
Panel D: Married Filing Jointly without Social Security benefits (left, N=382)



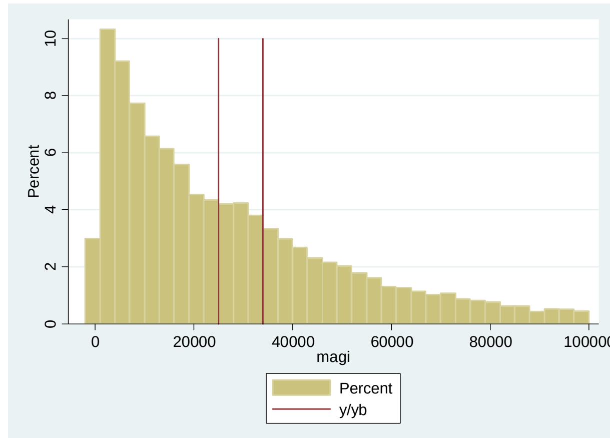
Source: Authors' calculations from the HRS.

Figure 3: Distribution of MAGI by taxpayer type and Social Security benefit receipt, SOI

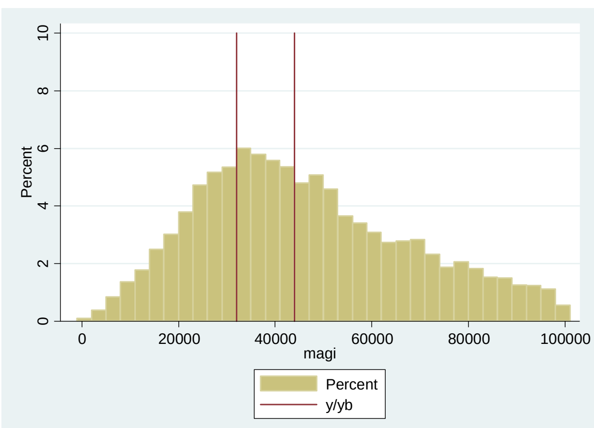
Panel A: Singles with Social Security Benefits



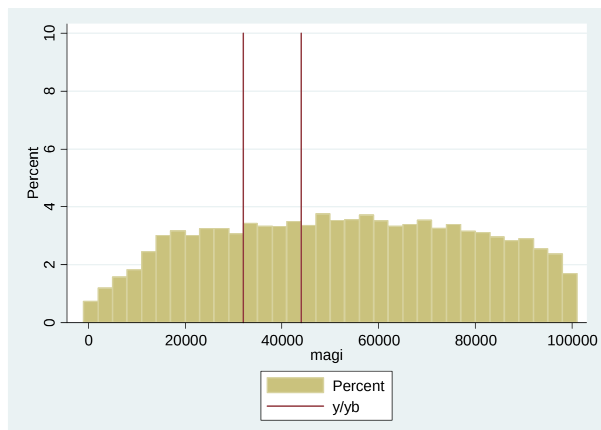
Panel B: Singles without Social Security Benefits



Panel C: Married filing Jointly with Social Security Benefits



Panel D: Married filing Jointly without Social Security Benefits



Source: Authors' calculations from the 2006 *SOI* public use file.

Table 1: Sample Selection Criteria

	wave 6 (2002)	**wave7 (2004)**	**wave 8 (2006)**	**wave 9 (2008)**
Interviewed in wave	18,167	20,129	18,469	17,217
66< age <75	5,325	5,482	5,725	5,961
Not self-employed	4,934	5,055	5,331	5,493
Has hours worked reported	4,884	4,990	5,252	5,441
Wage available (not imputed)	4,772	4,878	5,159	5,315
Has Marital Status	4,509	4,579	4,803	4,903
Is not receiving or applying for SSDI or SSI	4,504	4,573	4,793	4,896
Total across waves	18,766			
Has all control variables	**14,108**			

Table 2: Descriptive Statistics- Subsample still working

MARITAL STATUS	#	%
Single	704	34.26
Married	1,351	65.74
GENDER		
Male	1,016	49.44
Female	1,039	50.56
RACE		
Non-white	396	19.27
White	1,659	80.73
EDUCATION LEVEL		
<HS *(excluded)*	346	16.84
= HS	763	37.13
<College	446	21.7
>=College	500	24.33
HEALTH STATUS		
Excellent *(excluded)*	300	14.6
very good	759	36.93
good	700	34.06
fair	259	12.6
poor	37	1.8
JOB OCCUPATION		
white collar *(excluded)*	1,188	57.81
blue collar	867	42.19
JOB INDUSTRY		
labor intensive	282	13.72
less labor intensive	944	45.94
professional services	718	34.94
public administration	111	5.4
HOMEOWNERSHIP		
No	329	16.01
yes	1,726	83.99

Table 3: Descriptive Statistics- Subsample still working (continued)

Variable	Obs	Mean	Std. Dev.	Min	Max
Hours worked	2055	1378.625	745.3864	4	4576
Age	2055	69.13869	2.636486	66	75
Number of dependents	2055	0.121655	0.446553	0	5
Net wage (1k)	2055	18.1351	145.6671	0.271594	6187.643
Gross wage (1k)	2055	24.99837	196.7476	0.294092	8333.333
	2055	48.31034	91.04125	0	3597.228
virtual income	2055	0.243022	0.133271	-0.32445	0.586379
τ	2055	61.8729	136.3628	0	5179.682
MAGI	2055	1378.625	745.3864	4	4576

Source: Author's calculations. All wage and income statistics are presented in thousands of in 2007 real dollars.

Table 4: Social Security Claiming Age, by MAGI after FRA

Distance from first taxation Kink-Point	Average age at Interview	Average age Claimed Social Security	Average MAGI	Percent receiving Social Security benefits	N
-20,000-30,000	66.49	62.99	$7,817	86.7	294
	(0.50)	(1.30)	(3730)		
-10,000-20,000	66.51	63.11	14,448	90.1	465
	(0.50)	(1.29)	(5546)		
-10,000-0	66.51	63.11	25,812	92.1	330
	(0.50)	(1.23)	(5369)		
0-10,000	66.50	63.29	35,789	87.5	265
	(0.50)	(1.33)	(5430)		
10,000-20,000	66.45	63.44	47,118	91.5	201
	(0.50)	(1.38)	(4604)		
20,000-30,000	66.50	63.61	56,530	90.2	143
	(0.50)	(1.52)	(5132)		

Source: Authors' calculations from the HRS and Social Security Earnings history data. Standard errors are in parentheses.

Table 5: Difference in Difference Estimation for Social Security Claiming Age

	"Treatment 1"		"Treatment 2"	
VARIABLES	(1) Low income	(2) High income	(3) Low income	(4) High income
Post	-1.158397***	-0.727388**	-1.014747***	-0.963806***
	(-5.18)	(-2.27)	(-4.92)	(-2.87)
Treated	0.106708	-0.359200	-0.440295	-0.169647
	(0.49)	(-1.05)	(-0.75)	(-0.44)
Post*Treated	0.145147	-0.022706	0.043019	-0.012116
	(0.48)	(-0.05)	(0.05)	(-0.02)
Education level				
=HS	0.826805***	-0.568493**	0.713036***	-0.249148
	(4.44)	(-2.16)	(4.00)	(-0.86)
< College	1.020326***	0.424103*	0.949321***	0.754036***
	(4.48)	(1.69)	(4.28)	(2.97)
>= College	0.998018***	0.175743	0.881705***	0.461575
	(3.02)	(0.62)	(2.89)	(1.61)
Female	-0.368747**	0.175655	-0.346351**	0.211088
	(-2.29)	(0.93)	(-2.30)	(1.01)
Race(White)	-0.142927	0.268189	-0.013566	0.083360
	(-0.65)	(0.78)	(-0.06)	(0.29)
Married	0.751563***	0.509316	0.747668***	0.631670
	(4.55)	(1.47)	(4.55)	(1.61)
age	0.402067	0.398226	0.425424	0.311243
	(0.69)	(0.48)	(0.75)	(0.36)
age^2	-0.001493	-0.001866	-0.001785	-0.001023
	(-0.38)	(-0.33)	(-0.46)	(-0.17)
Virtual income	0.026996***	0.002950	0.022651***	0.000829
	(4.52)	(0.88)	(3.74)	(0.21)
Virtual $income^2$	-0.000064***	-0.000004	-0.000054**	-0.000002
	(-3.23)	(-1.08)	(-2.39)	(-0.43)
Constant	39.977513*	43.719296	39.828714*	45.714705
	(1.88)	(1.43)	(1.92)	(1.44)
Observations	3,504	1,904	3,864	1,544
R-squared	0.051	0.027	0.042	0.033

Source: Author's calculations from the HRS. Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust standard errors are in parentheses.

Table 6: Labor Supply Probit Results

VARIABLES	LFP
age	-0.315327
	(-1.14)
age^2	0.001651
	(0.84)
Married	0.174715***
	(-4.36)
Female	0.135486**
	(2.49)
Married*Female	0.209995***
	(3.29)
White	-0.078721**
	(-2.08)
N of Dependents	0.109906***
	(3.72)
Education	
=HS	0.070485*
	(1.70)
<College	0.175114***
	(3.60)
>= College	0.163597***
	(3.03)
Health	
Very Good	0.181151***
	(-3.90)
Good	-0.315777***
	(-6.76)
Fair	-0.594776***
	(-10.98)
Poor	-1.091431***
	(-12.56)
Blue collar Occupation	0.170512***
	(4.93)
Job Industry	
Less labor intensive	0.586403***
	(14.40)
professional services	0.675239***
	(14.31)
Public Administration	0.251131***
	(3.82)
homeowner	-0.036549
	(-0.90)
Constant	12.868334
	(1.33)
Observations	14,086
Pesudo R-squared	0.0963

Source: Author's calculations from the HRS. Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Presented in the table are coefficients of the probit model and robust z-statistics are in parentheses. Also included are wave dummies and census division dummies.

Table 7: Hours Worked Results

	OLS	Bracket IV	Level of Attachment IV			FE-IV
VARIABLES	(1)	(2)	(3) Full sample	(4) Female	(5) Male	(6)
Ln (net wage)	-0.133623*	0.411131*	0.002042	0.206035	-0.261380	0.238230
	(-1.92)	(1.69)	(0.02)	(1.62)	(-1.60)	(0.93)
Ln (virtual income)	-0.053100	-0.121619*	-0.186183***	-0.1737***	-0.2255***	-0.035954
	(-1.17)	(-1.77)	(-3.91)	(-2.85)	(-2.80)	(-0.55)
age	-0.912128**	-0.655390	-0.810245**	-0.640931	-0.9440*	0.189713
	(-2.46)	(-1.62)	(-2.21)	(-1.30)	(-1.74)	(0.51)
age^2	0.006162**	0.004647	0.005651**	0.004406	0.006617*	-0.000792
	(2.33)	(1.62)	(2.16)	(1.25)	(1.70)	(-0.35)
Married	-0.037199	0.091725	0.144689*	-0.089314	0.215422**	0.512813**
	(-0.56)	(1.03)	(1.87)	(-1.16)	(2.09)	(2.10)
Female	0.234409***	0.176827**	0.216654***			
	(3.34)	(2.20)	(3.02)			
Married*Female	-0.080083	-0.257896**	-0.229592**			-0.486219
	(-0.94)	(-2.41)	(-2.35)			(-1.61)
Education						
=HS	-0.148123***	-0.15294***	0.149025***	-0.077613	-0.24456***	
	(-3.10)	(-2.88)	(-3.03)	(-1.11)	(-3.55)	
<College	-0.064912	-0.150883*	-0.080884	-0.077888	-0.118603	
	(-1.14)	(-1.86)	(-1.28)	(-0.93)	(-1.25)	
>= College	-0.194633***	-0.37588***	0.219273***	-0.226846**	-0.187664	
	(-2.80)	(-2.93)	(-2.76)	(-2.08)	(-1.59)	
Health						
Very Good	-0.118723**	-0.019175	-0.053056	-0.119150	-0.010357	0.265862
	(-2.06)	(-0.27)	(-0.85)	(-1.43)	(-0.11)	(1.36)
Good	-0.093104	0.053758	0.008864	-0.020395	0.039388	0.574731*
	(-1.63)	(0.59)	(0.12)	(-0.18)	(0.37)	(1.74)
Fair	-0.085811	0.200032	0.113844	-0.104705	0.359813**	1.246956*
	(-1.35)	(1.32)	(0.92)	(-0.55)	(2.11)	(1.96)
Poor	-0.090178	0.358363	0.266529	0.005885	0.533480*	2.151193*
	(-0.78)	(1.34)	(1.15)	(0.02)	(1.71)	(1.81)
Blue collar occupation	-0.064204	0.000302	-0.099329*	0.048171	-0.23289***	-1.39534***
	(-1.45)	(0.00)	(-1.65)	(0.60)	(-2.77)	(-2.93)
Job Industry						
Less labor intensive	-0.253600***	-0.40829***	-0.441234***	-0.201199	-0.73653***	-1.324730*
	(-4.83)	(-3.08)	(-3.56)	(-1.20)	(-3.81)	(-1.85)
professional Services	-0.257764***	-0.52204***	-0.493962***	-0.298404	-0.72922***	-0.120513
	(-4.62)	(-3.43)	(-3.52)	(-1.51)	(-3.36)	(-0.14)
public administration	-0.274009**	-0.38629***	-0.347545***	-0.106914	-0.72277***	
	(-2.29)	(-2.89)	(-2.83)	(-0.78)	(-2.97)	
Social Security Benefit	0.000017***	0.000009	0.000020***	0.000013**	0.000032***	0.000006
	(4.19)	(1.03)	(4.22)	(2.11)	(4.07)	(1.09)
IMR		-0.568209**	-0.468861**	-0.269430	-0.679327**	-2.851823**
		(-2.09)	(-1.98)	(-0.72)	(-2.00)	(-2.10)
Constant	41.211005***	30.662636**	37.419168***	31.041609*	43.140014**	
	(3.16)	(2.13)	(2.91)	(1.79)	(2.27)	
Observations	2,054	2,054	2,054	1,038	1,016	1,423
R-squared	0.085	.	0.071	0.042	0.090	-0.007
Number of ind.	1192	1192	1192	608	584	561

Source: Author's calculations from the HRS. Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust z-statistics are in parentheses. Also included are wave dummies and an indicator for Caucasian (which is insignificant), and number of dependents (only significant in OLS (coef=0.12), zstat=3.5).

Table 8: Difference in Difference Estimation for Hours Worked

	"Treatment 1"		"Treatment 2"	
VARIABLES	(1) Low income	(2) High income	(3) Low income	(4) High income
Post	1.606099	42.807920	-4.918015	66.424065
	(0.11)	(1.13)	(-0.36)	(1.54)
Treatment	122.819397***	-122.752354***	187.440370***	-59.073322
	(2.97)	(-2.66)	(2.66)	(-0.81)
Post*Treatment	**-85.723778***	**76.469821**	**-73.326258**	**41.890700**
	(-1.94)	**(1.37)**	**(-0.88)**	**(0.46)**
Education level				
=HS	27.928847**	-46.531061	11.309623	22.523293
	(2.29)	(-0.93)	(0.88)	(0.40)
< College	35.115331**	-23.369084	20.490145	50.314993
	(2.20)	(-0.46)	(1.26)	(0.85)
>= College	63.278878***	-49.314592	26.277463	17.705593
	(2.69)	(-1.02)	(1.31)	(0.33)
Female	43.646674***	122.847447***	37.595166***	146.858530***
	(3.50)	(4.71)	(3.12)	(4.88)
Race(White)	-8.355202	-121.473045**	-0.045805	-108.250736*
	(-0.55)	(-2.00)	(-0.00)	(-1.66)
Married	-15.645202	-140.565231***	-11.041621	-138.284041***
	(-1.21)	(-3.71)	(-0.90)	(-3.16)
age	-69.415538	-484.523147***	-81.079567*	-548.711722***
	(-1.63)	(-4.47)	(-1.94)	(-4.33)
age^2	0.414176	3.027814***	0.491122*	3.429619***
	(1.46)	(4.16)	(1.76)	(4.04)
Virtual income	-1.285794***	-1.706161***	-1.074620***	-2.187912***
	(-4.78)	(-4.20)	(-4.27)	(-4.85)
Virtual $income^2$	0.001060***	0.001624***	0.000881***	0.002129***
	(4.59)	(3.11)	(4.14)	(3.71)
Constant	2,922.613517*	19715.863434***	3,374.884168**	22188.077751***
	(1.83)	(4.89)	(2.16)	(4.71)
Observations	3,866	2,064	4,234	1,696
R-squared	0.032	0.106	0.031	0.118

Source: Author's calculations from the HRS. Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Robust z-statistics are in parentheses.

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